UiO : Faculty of Law
University of Oslo

A Data-Driven Problem

Exploring Predictive Policing with Random Forest Crime Mapping in Oslo

Candidate number: 18

Submission deadline: May 2023

Number of words: 38,465

Abstract

Title: A Data-Driven Problem: Exploring Predictive Policing with Random Forest Crime Mapping in Oslo

By: Victoria Jerstad Stensland

Supervisors: Annica Allvin, Sveinung Sandberg

Department of Criminology and Sociology of Law, University of Oslo, Spring 2023

As technology advances at an unprecedented pace, law enforcement faces the challenges of keeping up to date with cutting-edge methods to develop effective crime prevention practices. Using crime mapping and algorithms such as random forest to inform the development of crime prevention policies has the potential to reduce instances of violent crimes in Oslo significantly. The interest in predictive policing is increasing, but when it comes to new technologies that can help explore crime patterns, supervised machine learning models are empirically tested in Norway to a limited extent. Since the risk of biased assessments based on crime predictions can increase when technologies are not adequately understood and the applied input data quality could be better, expanding our knowledge in this field is crucial. This study evaluates the predictive performance of random forest models forecasting violent crimes at three different spatial levels in Oslo, Norway. Data from the Norwegian police crime registry and environmental features, including urban data and weather data, are used to enhance the prediction performance of the algorithm. Findings showed that random forest could predict violent crimes with up to 80 per cent accuracy. Here, the location and spatial time lags of violent crimes in Oslo were significant predictors of future crimes, as were environmental features such as minor roads, residential areas, and forests. These results suggest that violent crimes in Oslo exhibit spatiotemporal dependencies, which can increase the risk of near-repeat offending and contribute to further occurrences of violent crimes. The study concludes that using random forest algorithms in crime mapping is a highly accurate predictive model for law enforcement in Oslo. Still, there are some critical challenges that technological advancements may present for the implementation of new policies. Based on the empirical findings and a more comprehensive discussion of the effectiveness, limitations, and ethical implications of the approach, this study hopes to contribute to the current discourse on the responsible and effective adoption of data-driven strategies in crime prevention, acknowledging the need for adaptability and continuous learning in the face of ever-evolving technology.

***Keywords*:**

Predictive policing, environmental criminology, machine learning, random forest, GIS, crime patterns

Acknowledgements

This thesis stands as a testament to unwavering dedication, relentless effort, and utmost persistence. The magnitude of the workload invested may not be fully captured within these pages. I willingly embraced the challenge of mastering a new coding language and statistical method, fearlessly venturing into unfamiliar territories to ensure the successful completion of this thesis. I wish to express my sincere gratitude to my thesis supervisor, Annica Allvin, for her extensive knowledge, support, and admirable patience that have made this journey an incredibly enriching learning experience. Her insight and guidance have shaped this project, making it significantly more meaningful than it would have been otherwise. I extend heartfelt thanks to my partner, whose support, and profound confidence in my potential have been paramount for my success. His encouragement has been a beacon in challenging times, a force that should never be underestimated. Further, I owe a debt of gratitude to my supervisor group, led by Sveinung Sandberg. This group has graciously devoted their time, offering invaluable feedback and advice, contributing significantly to my project. Graduating from the University of Oslo would be incomplete without acknowledging my friends and colleagues. Their steadfast support and solidarity have been a constant source of strength and inspiration. Our lively lunch breaks, daily quizzes, and stimulating discussion in reading room 7123 have created memories that I will cherish forever. In this moment of achievement, I extend my sincere thanks to everyone who believed in me and stood by my side throughout my time as a student. Finally, I would like to express gratitude to Oslo Forskning for providing the funding that made this study possible.

Thank you.

Table of Contents

List of Figures

List of Tables

List of Equations

Introduction

Technology's rapid advancement can present opportunities and challenges for law enforcement agencies as they strive to adopt innovative methods like *predictive policing* (Sandhu and Fussey, 2021). Predictive policing, as described by Mcdaniel and Pease (2021b), is a new concept involving data and technology used to generate statistical predictions about crimes. These predictions can then expand the policing landscape, inform new policies targeted at preventing crime in society, and capture the spatial and temporal dynamics associated with hotspots and policing of violent criminal behaviour (Mohler, Raje, Carter et al., 2018; Sandhu and Fussey, 2021). Intelligence received from predictive policing can be utilised to monitor crimes by mapping their spatiotemporal location and to improve patrol planning and resource management. It is worth noting that crime at place has historically received little focus in the criminological literature (Weisburd, Eck, Braga et al., 2016). Therefore, by understanding the criminogenic environment and how spatial crime mapping can contribute to helping law enforcement and policymakers develop targeted policies to prevent and reduce crime, this study may contribute to safer and more secure cities overall. Therefore, changing the direction of criminology and steering it towards *environmental criminology* could contribute to solving the crime problem (Felson, 2017). In this context, environmental criminology does not include the study of toxic dumping, state crimes or any other green criminological theories (Felson and Boba, 2010). Instead, environmental criminology focuses on the *criminology of place* by studying where, when, and why crimes happen and how to prevent them by focussing on criminal events' spatial, temporal, and social characteristics (Andresen, 2020). Environmental crime analysis involves examining and describing the criminogenic environment, crime patterns, sociodemographic characteristics, and details about the timing and location of crimes.

Predicting violent crimes can be more challenging than predicting burglary or other crime types due to their unpredictable nature (Shapiro, 2021). The explicit focus on violent crimes in this thesis is motivated by the fact that spatial crime patterns vary between crime types and that studying too many crime types, or not being crime specific in research, can lead to non-generalisable findings, as different factors may trigger each crime type (Brantingham, Brantingham and Andresen, 2017). The literature review and methodological section will further define and explain how violent crime can be distinct from other crime categories.

Moreover, this thesis introduces environmental crime analysis and the use of machine learning for predictive policing. It further discusses the ethical implications, limitations, and fairness in using advanced statistical tools. Thus, the main objective of this thesis is to discuss why predictive policing can be significant, how it can be applied, as well as addressing contemporary issues that might transpire when using this technology. Additionally, this research will examine rational choice, routine activity, and crime pattern theory as theoretical frameworks to explore why, where and when a violent crime is more likely to happen. Applying these frameworks can provide valuable insights into violent spatiotemporal crime patterns and identify areas that are more vulnerable to violent criminal activities. Additionally, this thesis will briefly introduce temporal constraint theory, social disorganisation, and Chicago school of sociology to further contextualise the research findings. The subsequent paragraph introduces the theoretical frameworks that the literature review will further elaborate upon.

The first theory, rational choice, suggests that offenders structure decisions regarding criminal offences by rationalising the risks and rewards associated with crimes (Cornish and Clarke, 1987). In environmental criminology, it is hypothesised that a rational choice can be deliberate and influenced by the immediate environment or criminogenic features in the offenders' activity or awareness space (Sidebottom and Tilley, 2017). However, some scholars challenged the assumption of full rationality, arguing that offenders may exhibit bounded rationality and overlook potential targets due to laziness (Carroll and Weaver, 1986). The second theory, routine activity, builds upon rational choice theory by explaining how the decision-making process can be tied to routine activities when offender and target comes together in time and space (Andresen, 2010). According to the routine activity theory, crime is dependent on three essential elements, which form a crime triangle. Cohen and Felson (1979) propose that a crime can only happen when a motivated offender interacts with a target in the absence of capable guardians. Furthermore, Sherman, Gartin and Buerger (1989) discovered that low social control significantly influences the prevalence of crime within society. Consequently, employing the routine activity approach to analyse patterns of violent crimes in Oslo can provide valuable insight into movement patterns and the relationship between crimes and routine activities. The final theoretical perspective, crime patterns, combines routine activity and rational choice theory, investigating the patterns and trends of crime in society. This theory is significant for this research because it can help explain the offenders' daily movement patterns by identifying why the offender and suitable targets were brought together (Brantingham et al., 2017; Townsley, 2017). Moreover, the crime pattern theory can be used to understand the environmental backcloth of society that can contribute to criminogenic crime attractors or generators.

Furthermore, this thesis examines how predictive policing technologies can result in a negative feedback loop making it more difficult for the police to collaborate with the population, potentially harming a community's willingness to contribute to crime prevention. Although AI can be used in predictive policing practices for crime prevention, the notion of objectivity does not always match reality as this technology may cause more harm than good, specifically considering social inequalities and pre-existing biases (Moravec, 2019 in Mcdaniel and Pease, 2021b). While crime prevention techniques may reduce violent crimes in society, the data-driven problem relates to the possibility of increasing bias and issues of fairness when using AI and aggregated data for predictive policing (Mcdaniel and Pease, 2021b). Therefore, Richardson, Schultz and Crawford (2019) contend that AI-based technologies should not be carelessly implemented.

Research objective

This quantitative master thesis explores the connection between environmental criminology, machine learning and the distribution of violent crimes in Oslo. Previous studies have demonstrated that spatial crime mapping using GIS and supervised machine learning, such as random forest models, could provide the most accurate prediction of crime patterns compared to other models (Alves, Ribeiro and Rodrigues, 2018; Berk, 2010; Oh, Song, Park et al., 2021). Using quantitative techniques for this purpose can help improve policies and decision-making through prediction and pattern recognition (Araújo, Cacho, Bezerra et al., 2018). Therefore, to examine whether predictive policing technology can be employed to predict the spatiotemporal violent crime patterns in Oslo, this study utilises a combination of GIS and random forest. It conducts an empirical analysis focussed on assessing the accuracy of this technology across various spatial levels. The study aims to contribute to the discourse on responsibly employing data-driven technology for predictive policing and crime prevention by discussing the limitations, ethical considerations, the need for adaptability and continuous learning to stay up to date with ever-evolving technology. To perform the random forest analyses, this thesis applies data from the police criminal register (STRASAK) combined with environmental features from Open Street Map (OSM) and weather data from the meteorological institute (MET). Explicitly, the research questions of this thesis state:

Research questions:

1. *To what extent can integrating environmental criminology and supervised machine learning through random forest models enhance the accuracy of crime prediction?*

2. *What are the critical considerations for its effective implementation in the context of predictive policing?*

Thesis structure

The structure of this thesis separates into six sections. Following the introduction, the literature review presents previous research in environmental criminology, crime prevention through environmental design, application of machine learning in criminology, and potential limitations in predictive policing. This review identifies potential gaps in current knowledge and justifies the necessity for this research. The literature review introduces theoretical frameworks that can serve as a foundation for this research.

Following the literature review, the methodological section will outline this research's statistical procedures, including ethical considerations and measures to endorse transparency, reliability, and validity of this thesis. This chapter includes a map, explaining the geography of Oslo.

Following the methodology, the result section provides evidence to support the research objectives for this thesis by presenting the findings and outcomes of this study.

Following the results, the discussion critically evaluates the research findings compares to previous studies separated into three sections where the first part explain draws on relevant literature to explain the necessity for using predictive policing for predicting violent crimes. The second part of the discussion considers the findings of the supervised machine learning and assess whether this statistical method is viable for crime prediction. In the third section, the discussion considers the limitations of using predictive policing for crime mapping and highlights the essentiality of balancing objectivity and subjectivity to avoid systematic errors. Subsequently, there is a section considering who the implementation of AI can benefit. Finally, I will reflect upon potential limitations for the current study and embrace opportunities for future research within this field.

Following the discussion, this thesis will conclude that despite potential limitations, supervised machine learning through random forest and GIS proves valuable as a supplementary tool in decision-making for law enforcement agencies and has the potential to create safer communities by effectively preventing violent crimes in Oslo.

Concept clarification

This concept clarification section concisely explains essential terms that can assist readers with limited statistical knowledge specific to the context of this thesis and may vary from other interpretations in the field.

Crime mapping in the context of this thesis place criminal events on the map using geographical coordinates and identifies spatiotemporal patterns linked to violent crimes.

Artificial Intelligence (AI) in predictive policing is a digital tool that surpasses human intelligence, can identify hotspots and patterns in crime data, and can improve the efficiency of police work.

Machine learning is a subset of AI that involves using algorithms to automatically learn patterns in the data without being explicitly programmed.

Algorithms are, in this thesis, understood as a sequence of instructions used in machine learning to build a model that automatically improves through experience.

Random forest is a supervised machine learning algorithm that combines decision trees to make predictions and classify data.

Geocoding is a crucial step in crime mapping and involves converting an address into a point on a map by assigning geographic coordinates.

Geographical Information Systems (GIS) is a tool used to explore, manipulate, and analyse the spatial relationships in the data.

Literature Review

Established research has shown that crime follows patterns in time, space, and society rather than occurring randomly (Alves et al., 2018; Andresen, 2008; Newton and Felson, 2015; Ratcliffe, 2010; Weisburd et al., 2016; Wortley and Townsley, 2017). Uniformity seems indefensible when observing patterns from criminal events because there are many reports of hotspots, cold spots, and a high repeat of offenders and victims (Brantingham et al., 2017). Consequently, Brantingham et al. (2017) contend that the argument for complete randomness of targets or location is no longer plausible. As a result, studying crime patterns and examining the temporal and spatial factors behind where and when crime clusters can provide valuable insights into criminal behaviour. This literature review explores previous research and theoretical frameworks in environmental criminology, aiming to provide valuable insights for the advancement of crime prevention policies. These theoretical frameworks include rational choice, routine activity, and crime pattern theories while supplementing the understanding of violent crime's temporal and spatial patterns with temporal crime theory. Environmental criminology, in the context of this thesis, studies factors that bring the offender and target together in time and space and can help explain the distribution, characteristics and the offender's selection of crime sites (Bruinsma and Johnson, 2018; Morris and Mannheim, 1957). Furthermore, these theories can also provide valuable insight for predicting and preventing violent crimes yet to be committed. Used with a focus on formal social control, this kind of study and the practice based on them is often known as predictive policing (Sandhu and Fussey, 2021).

According to Morris and Mannheim (1957), crime can be influenced by the offender's attachment to, or perception of, a place's social and physical characteristics. Analysing the temporal and environmental influence on crime could, therefore, be a pivotal contribution to law enforcement and policymakers by informing them on the development of effective strategies for forecasting, preventing, and addressing violent criminal behaviour and events (Wortley and Townsley, 2017; Zhang, Liu, Xiao et al., 2020). Conventionally, predictive policing and crime mapping have been employed to identify spatial and temporal patterns linked to the emergence of *criminal hotspots* and to help direct the police in response to reducing crime rates (Mohler et al., 2018). Criminal hotspots are areas where crime can be highly concentrated and have previously been found to cluster at street addresses, segments, or intersections, as well as in areas with specific *criminogenic* characteristics (Braga and Clarke, 2014; Brantingham et al., 2017; Deryol, Wilcox, Logan et al., 2016; Newton and Felson, 2015). The specific criminogenic characteristics of an area may be defined by their ability to conducive criminal activity and display the potential for criminal behaviour influenced by situational factors (Groff and Lockwood, 2014; Wortley and Townsley, 2017). Therefore, identifying and understanding these characteristics of criminogenic environments while being aware of spatial crime patterns makes it possible to investigate, control and prevent crime by addressing the factors contributing to crime in a given location (Wortley and Townsley, 2017).

Towards a geographical imagination

The sociological imagination focuses on understanding individuals' social context, deviations, backgrounds and how they relate to social structures, changes, and stratifications (Mills, 2000[1959]). It also examines people's movements and the direction of social change (Brantingham and Brantingham, 1991). A geographical imagination, on the other hand, considers crime and its patterns within space and time (Brantingham and Brantingham, 1991). According to Eck (2003), understanding how people interact within specific environments can lead to more effective solutions for preventing future criminal behaviour. Previously, the focus in criminology has primarily centred around the interaction between offender and target. However, it is equally important to acknowledge that the crime problem can be connected to social behaviour and environmental factors (Eck, 2003). The *crime triangle* suggests that crimes are more likely to occur when the offender and target come together in a situation where capable guardians are absent or fail to act, illustrating how crime can be connected to the environment (Cohen and Felson, 1979). By implementing the crime triangle in a geographical approach, it can become possible to connect criminal patterns with routine activities to prevent and predict locations of future crime events within a space-time coordinate system (Felson, 2017; Felson and Boba, 2010; Tillyer and Eck, 2011). Similarly, with the rapid development of technologies within the policing landscape, the geographical approach to studying crime has led scholars to develop interventions to prevent crime at place (Anselin, Cohen, Cook et al., 2000; Weisburd et al., 2016).

On that note, Weisburd et al. (2016), Felson (2017), and Brantingham et al. (2017) contend that scholars within the sociological imagination have been overly concerned with isolated crime events and that they sometimes disregard the insights into crime prevention acquired through studies on the geographical distribution of crime. A more significant focus on spatial and temporal crime pattern analysis could contribute to the criminological discipline by addressing the research gap between isolated crimes and recurring crime events that are affected by time or place (Brantingham et al., 2017; Weisburd et al., 2016). Moving beyond the traditional crime perspective on individual offenders' social context and background, preventing and predicting crimes facilitated by routine activities or rational choice may become possible. This claim is supported by previous research concerning the relationship between spatial factors and crime patterns, and based on findings that crimes can be shaped by routine activities, rational choice, or other criminogenic factors (Felson, 2017; Tillyer and Eck, 2011; Wortley and Townsley, 2017).

Neglecting previous research that suggests the role of environmental factors in crimes may lead law enforcement and policymakers to focus more on minority groups or delinquents as potential offenders based on their individual characteristics. Criminologists with a geographical imagination could, therefore, contribute with complementary knowledge that can lead to more effective strategies to understand, control, and reduce crime by shifting the units of analysis in criminology and considering the importance of geographical features of crime (Weisburd, 2015; Weisburd et al., 2016). Brantingham and Brantingham (1991) argue that it can be crucial to acknowledge that violent crimes can occur with equal frequency in unexpected areas, underlining the weight of environmental factors in crime prevention strategies. For example, suppose a violent crime is committed by someone with a minority or middle-class white background close to their respective homes. These crimes would be treated as unrelated in the sociological imagination but as equivalent in the geographical imagination, assuming that the spatial environment has potential to increase criminal activities (Brantingham and Brantingham, 1991). Consequently, embracing a more geographic perspective can contribute to a change in the criminological field where new technological tools can be utilised to provide transparent policework that is subjective to economic, efficient and effective measures (Mcdaniel and Pease, 2021b).

Despite the advancement of spatial crime analysis in environmental criminology, using data to predict future locations of crime events can result in a biased and unfair targeting of socially deprived areas, where poor living conditions are more concentrated due to socioeconomic factors such as poverty, inadequate social support and a lack of resources (Brantingham, Valasik and Mohler, 2018; Mohler et al., 2018; Weisburd et al., 2016). This unfair targeting of areas is supported by Mohler et al. (2018), who contend that racial discrimination in predictive policing could increase arrests of minority populations. Thus, assuming social deprivation is connected to ethnicity, ethnic minorities are more likely to be controlled by law enforcement, and when this data from these areas are used for crime prediction, it may produce further apprehensions because the police are repeatedly sent back to these locations. Kaufmann, Egbert and Leese (2019) suggest that pattern-based crime predictions feed back into cultures of policing and can reinforce a specific way of thinking about crime and offenders.

Spatial crime mapping

Within environmental criminology, the concept of *crime at place*, introduced by Sherman et al. (1989), refers to the premise of ecological crime. This premise builds upon Cohen and Felson's (1979) crime triangle, which suggests that an increase in the risk of criminal activity *in a place* may occur when a potential offender, a suitable target, and a lack of capable guardians cross over in time and space. Sometimes capable guardians are police officers or others performing formal social control, protecting targets of crime by preventing opportunities for criminal behaviour. However, Felson (1986) emphasises that capable guardians are most likely ordinary people situated in the immediate area or passing by when a potential offender may be contemplating committing a crime. This bystander effect makes it possible to assume that informal social control can be an additional efficient control mechanism that makes people abstain from committing crimes. Nevertheless, informal social control will not always prevent crime. Sometimes offenders actively seek out their targets[1]; other times, victims are selected because their lifestyles or movement patterns overlap with the offenders in a specific location, known as a *node activity area* (Brantingham and Brantingham, 1993b). Brantingham and Brantingham (1993b) explain node activity areas as groups of locations in a city that share similarities and are seen as connecting points between travel paths and networks. By identifying the common characteristics of these areas, it could become possible to identify people's movement patterns and contribute to understanding how people move through a city. Similarly, an overlap in activity patterns for the offender and target may, according to Brantingham and Brantingham (1993b), increase the likelihood of victimisation. For this reason, anticipating where or when the next crime occurs can help inform law enforcement and policymakers to develop effective crime prevention strategies to create a safer community (Wang, Yin, Bertozzi et al., 2019).

[1] For example, for retribution or when the offender knows the target.

Mapping and comprehending violent crime patterns could lead to further crime prevention with various tactics such as targeted interventions and enhanced governance in high-risk areas. Routine activity and crime pattern theories, which will be discussed later in this chapter, suggest that if someone were to become a target of crime, it would likely happen in their primary activity space[2] (Brantingham and Brantingham, 1993b; Ratcliffe, 2012). Consequently, mapping crime patterns including frequently visited places, travel pathways, public transportation, recreational sites, work areas, and residential neighbourhoods, can help identify crime clusters and hotspots in a specific place where people commonly spend their time (Brantingham and Brantingham, 1993b). Gorr and Harries (2003) and Andresen (2008) suggest that an algorithmic approach to and visualisation of crime patterns through statistical analyses can be applied to inform innovative and effective crime management practices. Therefore, shifting the attention towards predictive policing can make it possible to capture the spatial and temporal dynamics associated with crime clustering and the policing of criminal behaviour (Mohler et al., 2018). Expanding upon this concept, this thesis aims to evaluate the prediction performance of a more advanced statistical tool that can be used for predictive policing.

In the predictive policing framework, it can be preferable to implement statistical analyses to handle the complexity of crime to ensure public safety. Monitoring crime patterns can improve patrol planning and resource allocations, specifically when using an algorithmic approach to provide information concerning places and times where there is a likelihood of increased criminal activity (Araújo et al., 2018). As technology advances, analytical methods specifically tailored to examine the effect of place have become increasingly prevalent (Anselin et al., 2000). Despite this development, there is a lack of consensus in the criminological literature on the appropriate methods for measuring and reporting the concentration of crime in specific locations (Alves et al., 2018; Andresen, 2008; Bernasco and Steenbeek, 2017). Accordingly, various statistical analyses have been used to predict crime distribution in multiple cities to explore if it is possible to improve decision-making through pattern recognition and crime prediction (Andresen and Malleson, 2011; Araújo et al., 2018; Berk and Bleich, 2013; Bowers, Johnson and Pease, 2004; Kounadi, Ristea, Araujo et al., 2020; Wang et al., 2019). This thesis will not aim to determine the superiority of a particular statistical method for analysing crime patterns. Instead, it will focus on whether it is possible to use supervised machine learning in

---

[2] See section *Crime Pattern Theory* in the literature review.

predictive policing and reflect upon the ethical and critical considerations for effectively applying crime pattern analysis.

The four dimensions of crime

The crime triangle mentioned earlier can be expanded into four key factors, or four dimensions, of a crime: a law, offender, target[3], and location (Brantingham and Brantingham, 1991). According to Brantingham and Brantingham (1991), there can be no crime without a combination of all four dimensions. The first dimension involves an examination of the legal framework surrounding a crime, including the creation, enforcement, fairness, and effectiveness of laws. The second dimension focuses on the individual characteristics and experiences, such as their motivations, behaviours, and other factors that may influence the decision to commit crimes. The third dimension considers the potential targets of crime. Finally, the fourth dimension of crime examines the spatial (and temporal) factors that may contribute to crime, which is the most central field of environmental criminology (Andresen, 2010). Seeing these four dimensions together can provide valuable information on the physical, social, and economic characteristics of the location where crime situates, as well as the social processes and dynamics that influence criminal behaviour in a specific environment (Brantingham and Brantingham, 1991). Therefore, it can be essential to keep all dimensions in mind and to understand the interplay of these dimensions to prevent future crime. While each element represented in these dimensions can point towards the understanding of criminogenic events and crime as a whole (Brantingham et al., 2017), the focus of this thesis is exclusively on the fourth dimension to further illuminate the possible limitations of crime mapping and predictive policing.

The emphasis on the fourth dimension, which involves analysing spatial and temporal patterns together with criminogenic factors, has become necessary to prioritise crime locations in Norwegian criminology. For example, Teknologirådet (2016), who provides advice to the Norwegian Parliament and the government on new technology, recommended the integration of predictive policing into policing practices. However, only a few previous studies, including Hoppe and Gerell (2019), Hart, Pedersen and Skardhamar (2019), Gerell (2021) and Gerell, Allvin, Frith et al. (2022) have had a spatial focus on crimes in a Scandinavian context. To the best of my knowledge, no previous studies have used a random forest algorithm to predict the

---

[3] In this thesis, the word target refers to individuals as victims.

spatial or temporal location of violent crimes in Norway. There is also an increasing focus on crime locations in Oslo politics and within the Norwegian police, alongside an interest by Norwegian officials in predicting future crimes (Andersen, Gerell and Hanssen, 2021; Larsson, Eriksen, Pedersen et al., 2022).

Environmental criminology in a historical context

The study of the relationship between crime and the environment has a long history. Early research by Quetelet (1842) and Guerry (1833) laid the foundation for contemporary environmental criminology (Andresen, Brantingham and Kinney, 2010; Brantingham and Brantingham, 1991; Eck and Weisburd, 2015). Already then, it was found evidence of various spatial relationships in the geographical distribution of crime suggesting that crime patterns vary by location and that there is a connection between reported crime rates, high population density, illiteracy, and poverty (Brantingham and Brantingham, 1991; Ratcliffe, 2010). However, it was in the 20th century that the field of environmental criminology experienced significant development, particularly through notable contributions of the *Chicago School of Sociology* and its focus on *social ecology* (Brantingham and Brantingham, 1991; Morris and Mannheim, 1957). As explained by Morris and Mannheim (1957), social ecology is a field of sociological inquiry that is interested in the connection between people and areas with high levels of criminal activity. In this thesis, social-ecological perspectives on crime considers the role of the physical environment, specifically the availability of potential targets, and routines that may bring offenders and crime opportunities together in a specific location and time. This idea is further developed in the concept of place-based theories, which examine how the overall social environment influences individual behaviour (Anselin et al., 2000). The growing interest in the connection between people and the criminal area drew crime prevention practitioners to seek out theories that could explain patterns related to demographical and geographical characteristics (Ratcliffe, 2010).

Chicago school of sociology

With a focus on social life and the arrangement of social actors in urban space and time, and how these factors can influence crime patterns in a city, the Chicago School of Sociology is mainly concerned with understanding the relationship between urban sociology and the natural area (Anselin et al., 2000). The natural area hypothesis suggests that neighbourhoods with specific physical and social characteristics, such as poverty, residential instability, and social disorganisation, are more likely to experience higher crime rates and other social problems (Abbott, 1997). This approach to studying crime was used to examine how crime rates may change within and between different community zones, how these patterns change through time and how they may be related to additional factors such as city expansion, population movements, and economic development (Shaw and McKay, 1942 in Ratcliffe, 2010). When studying crime patterns within a city, researchers have often employed a zonal approach. This approach, first developed by Burgess (1916), involves crime mapping in different circular zones of the city by examining their unique characteristics (Brantingham and Brantingham, 1991; Kirk, 2009; Morris and Mannheim, 1957; Shaw and Mckay, 1969). The natural area is a fundamental concept within the zonal approach, focussing on studying patterns and processes of social phenomena over time in specific geographic locations. In the context of crime analysis, it involves examining the temporal patterns of crime, exploring the potential impact of the physical and social environments on crime patterns, including the question of whether the environment can shape or divert crime (Abbott, 1997).

From the zonal approach in the Chicago school, it has generally been assumed that crime rates are higher in the city's core and decrease as one moves further away from the city centre (Brantingham and Brantingham, 1991). Shaw and Mckay (1969) found that measuring areas in square miles was a convenient way to calculate delinquency rates in Chicago. At this time, spatial analysis in the Chicago school required monumental time and resources because the data were often collected manually to be analysed (by hand) using specific geographic units such as census tracts, community areas, or one-square-mile areas of a city (Andresen et al., 2010; Anselin et al., 2000). They, and other scholars from the Chicago School, made significant contributions to our understanding of crime patterns in urban areas. In recent years, however, research in environmental criminology has shifted away from the zonal approach because it is argued that the concentric zone system is somewhat generalised and detached from reality (Harries, 1974; Morris and Mannheim, 1957). The generalisability of this approach is no longer applicable since it may not accurately represent areas that have not developed in a zonal manner. In other words, conclusions drawn from research on crime in Chicago may not be transferable to urban areas with distinct characteristics. Nevertheless, examining the urban area to acquire an essential complementary understanding of crime places might still be valuable. Consequently, the social disorganisation theory emerged from the Chicago school to analyse crime more closely in neighbourhood areas (Andresen, 2010). By considering how characteristics in these neighbourhoods can affect crime in general, this approach becomes more relevant for explaining crimes compared to the zonal approach.

Social disorganisation theory

The social disorganisation theory is an environmental perspective that emphasises social control as an efficient crime prevention mechanism, wherein the lack of collective efficacy in different areas is understood as one of the criminogenic features of places (Braga and Clarke, 2014; Deryol et al., 2016). Social disorganisation theory arose from the Chicago school as an attempt to explain crime rates with reference to the relationship between properties and characteristics of an area, the inability to establish a sense of community, and the lack of social control (Andresen, 2010; Kubrin and Weitzer, 2003; Weisburd et al., 2016). This theory, refined by Shaw and McKay (1942 in Weisburd et al., 2016), strongly emphasised the role of space when analysing crime patterns and examined how social structures in different urban areas could shape criminal behaviour and movement. Shaw and McKay (1969) questioned what structural factors contributed to delinquency in contemporary society. They found that the persistence of certain ecological features, such as residential instability, low socioeconomic status, and ethnic heterogeneity, were associated with social disorganisation. Similarly, research supports Shaw and McKay's (1969) findings that crime tends to be more prevalent in areas with societal problems (Andresen et al., 2010; Brantingham and Brantingham, 1991; Shaw and Mckay, 1969). For example, neighbourhoods with poor physical conditions, heavy industry, commerce, low socioeconomic status, diverse ethnicity, and where there is a high population turnover. Similar to the present thesis' focus, social disorganisation theory is not concerned with how personal characteristics can influence crime in an area. Instead, it is focusses on the fundamental relationship between neighbourhood characteristics and criminal behaviour within an area (Andresen, 2010). More specifically, Andresen (2010) argues that it is essential to thoroughly comprehend a place's areal structure to understand its relationship to crimes in these areas.

Social disorganisation theory differs from the theoretical perspectives in this thesis because of its unique focus on a community's inability to maintain effective social control and how neighbourhoods can influence or foster crime and delinquency (Kubrin and Weitzer, 2003; Sampson and Groves, 1989). When a place is socially disorganised, there is usually a lack of social cohesion and solidarity which can be considered critical mechanisms to reduce crime and public disorder (Kubrin and Weitzer, 2003). For example, neighbourhoods with high population turnover (such as those in a city) can face similar challenges when attempting to establish a sense of community since new residents may not have strong ties to the neighbourhood area or its history due to the frequent migration of people (Weisburd et al., 2016). Andresen et al. (2010) contend that social cohesion is necessary for residents to work together to address community issues and maintain a safe environment within a neighbourhood. Without an established sense of collective efficacy in a community, here understood as the ability to unite and work together to achieve a common goal, Andresen et al. (2010) argue that it can be difficult for residents to build relationships and take responsibility for the well-being of the community. Consequently, the lack of collective efficacy can negatively impact community efforts to prevent crime in an area because residents will be less likely to intervene.

To support the claim that low collective efficacy can negatively impact crime prevention, an empirical analysis of community structure by Sampson and Groves (1989) observed the social structure of 238 different communities in England and Wales. Sampson and Groves (1989) found that communities with low social organisation and participation, and unsupervised teenage peer groups, exhibited disproportionately higher crime rates. Additionally, they found that residents in socially disorganised areas were less likely to report criminal incidents, possibly because these residents had yet to learn the expected norms of the community and establish social cohesion. In sum, areas lacking social cohesion or social control could become more vulnerable to violent crimes and may be prime candidates for criminal activity to flourish (Weisburd et al., 2016). According to Jeffery (1969), urban planning can contribute to social cohesion in a neighbourhood by re-establishing human contact in these areas. Hence, when urban planners and architects design residential areas, they could consider creating an environment where social cohesion and collective efficacy is easy and natural to maintain. Then, knowing where or when violent crimes are more likely to happen, it could become possible to prevent crime through environmental design by manipulating the social space to encourage social cohesion or collective efficacy. For this reason, it can be essential to address social disorganisation at the neighbourhood and broader levels of a city by encouraging social cohesion and community engagement to establish informal social control mechanisms (Andersen et al., 2021; Kubrin and Weitzer, 2003). If reducing crime in socially disorganised areas fail, higher crime rates can trigger a cycle of further breakdown of the established community, resulting in further deterioration, ultimately turning the area into a crime hotspot (Braga and Clarke, 2014). Then, if these crime clusters are associated with anonymity and lower guardianship, it may point to a lack of informal social control (Anselin et al., 2000).

From both Sampson and Groves' (1989) and Shaw and McKay's (1969) findings, there is a positive correlation between crime and social problems or low collective efficacy; when one increases, so does the other. For example, Shaw and Mckay (1969) showed that when a neighbourhood was converted into an industrial area, upper-class individuals were likely to relocate as a consequence of hazardous or unappealing living conditions. This relocation and poor conditions would attract an influx of lower-income residents due to the decreased property values. Consequently, residents in these neighbourhoods experienced a lack of social cohesion, values, or norms, which made residents less empowered, able, or motivated to improve and advocate for better living conditions (Andresen et al., 2010; Shaw and Mckay, 1969). Subsequently, a neighbourhood may further deteriorate physically due to the thriving criminal activity, which is allowed to persist because of long-standing social traditions tied to the daily lives of residents and the absence of social control. Based on these arguments, it is possible to assume that having no social ties to a community can contribute to increasing the likelihood of residents relocating to other areas, thereby creating residential instability due to high-population turnover and low collective efficacy. Albeit this thesis will not focus on individual crime events, socioeconomic or sociodemographic traits, mapping where or when crime clusters can provide insights into the locations of neighbourhoods that experience high levels of violent crimes and may need increased guardianship, improved collective efficacy, social cohesion, or strengthening social bonds through spatial manipulation.

Understanding violent crimes

In the context of crime prevention, the distribution of crimes can vary depending on what type of crime is committed. As far back as the nineteenth century, researchers like Guerry (1833) and Quetelet (1842) noted differences in the distribution of violent crimes and property crimes (in Brantingham and Brantingham, 1991). Similarly, there are many reasons why the distribution of crimes may differ based on environment and opportunity. For example, Brantingham and Brantingham (1993b) claimed that the definitions of a "good" crime site and "suitable target" for *burglary* had been extensively tied to factors such as neighbourhood type, street network, site location, and more being identified as positive attractors to this specific crime type. Additionally, Xia, Stewart and Fan (2021) discovered that *drug* offences were more prone to occur in areas with vacant buildings. This association also varied depending on the type of drug offence committed. *Violent* crimes, on the other hand, have been found to exhibit certain characteristics associated with crime risk, such as proximity to street segments including bars, schools, public transport stations, and other non-residential facilities (Groff and Lockwood, 2014). Consequently, it makes sense to argue that different crimes have different offenders, motives, crime sites and suitable targets. Understanding the nature and defining the borders of a crime can, therefore, be fundamental for predicting and preventing these crimes (Cornish and Clarke, 2017; Jones, 2000). Cornish and Clarke (2017) contend that even subcategories of a crime type may be too broad for developing effective crime prevention techniques. This need for narrowing the criminological field may be one reason why it is essential to be crime-specific when attempting to understand or predict crime patterns.

By understanding the surrounding circumstances and frequency of a crime, Jones (2000) argues that it can become possible to implement strategies that are more effective for dealing with a specific crime type. Violent crimes can have devastating effects on both individuals and society, taking various forms such as abuse, assault, robbery, or acts of terrorism (Stene, 2017). Because the definition of a violent act can be socially constructed and shaped by norms, the perception of violent crimes might vary across cultures, countries or within groups in society at various times in different contexts (Brownstein, 1999; Jones, 2000). Consequently, suggesting effective crime prevention measures to address violent crimes becomes a challenging task, as what may be considered violent in one culture could be deemed acceptable behaviour in another. Therefore, in this thesis, the term *violence* is defined as the deliberate use of power to cause harm, threaten, or employ physical force against others (Kondo, Andreyeva, South et al., 2018).

An initial step towards understanding and preventing violent crimes would be to examine official government statistics on the prevalence of these crimes in an area or time period. Ratcliffe (2010) contends that knowing the monthly trends of violent crimes can aid in allocating resources and developing strategies to ensure public safety during months when the crime rate is increased. In his study, Ratcliffe (2010) found that violent crimes would increase during the summer season. Taking into consideration the discoveries outlined in Ratcliffe's (2010) research, it may be feasible to employ data analysis for predictive policing to allocate resources effectively and implement measures to ensure public safety when crime is more likely to happen. Explicitly, this thesis' definition of a violent crime includes a wide variety of physical acts ranging from minor bruises to serious bodily harm or death. Although these specific violent crimes will be further defined in the methodological section, it is important to highlight that some of the violent crimes studied in this thesis include cases of physical violence, threats, robbery, and deprivation of liberty, among others.

Theoretical frameworks

Understanding how the offender thinks and reasons in situations can be necessary for comprehending what the offender considers or ignores when contemplating crime (Felson and Boba, 2010). By studying how environmental factors can contribute to crime in a specific place, at a specific time, researchers could better understand the major causes of violent crime. They can thereby evaluate the potential for implementing policy interventions to prevent violent crimes in the predicted area (Brantingham and Brantingham, 1991). Previous studies in the criminological literature have explored the association between criminal activity and socioeconomic factors; however, limited attention has been given to the significance of temporal dynamics, specific geographical locations, crime types, and other crime-related features (Almanie, Mirza and Lor, 2015; Thomas and Drawve, 2018; Weisburd, 2015; Weisburd et al., 2016). To suggest how rational choice, routine activity, crime pattern, and temporal constraint theories can be applied to gain insight into the significance of geographical and temporal information, this thesis aims to address the violent crime problem more holistically. Although these theories complement each other, they provide unique explanations for why crime occurs in different locations (Eck and Weisburd, 2015). Additionally, this thesis will supplement with the following theoretical frameworks to address the contemporary data-driven problem of predictive policing.

Rational choice theory

With deep roots in the classic sociological tradition, the rational choice theory centres on the complex decision-making process within social and economic environments (Goldthorpe, 1998). By questioning the knowledge actors have, and how they apply this knowledge in situations to maximise utility and achieve their goals, rational choice theorists attempt to explain why individuals may choose one course of action over another (Goldthorpe, 1998). Presumably, the actor will consider every possibility on the spectrum of different options available, not just in the moment, but in the future as a whole and can be motivated by potential consequences and outcomes of each decision (Simon, 1983 in Goldthorpe, 1998). Furthermore, a rational choice theoretical perspective can provide a general framework used in situational crime prevention and deterrence to emphasise the criminal decision-making processes and their connection to the immediate environment (Cornish and Clarke, 1987). When there is an absence of capable guardians, potential offenders may structure their decision on whether to commit a crime based on a combination of factors. These factors can include the desire for a thrill from the widespread presence of opportunities or a desire for power and other risks and costs associated with committing a crime (Brantingham et al., 2017; Collins and Loughran, 2017; Cornish and Clarke, 1986; Cornish and Clarke, 2017; Matsueda, Kreager and Huizinga, 2006; Sidebottom and Tilley, 2017). The various impulses can suggest that when a motivated offender chooses their target, it is through a deliberate and rational thought process that considers the offender's overall assessment of the potential crime (Cornish and Clarke, 1987).

Employing rational choice theory when analysing violent crimes and offender patterns can be an important component for the development of opportunity perspectives and a key contribution to the study of predictive policing by evaluating the situated interactions between parties and the individual decision-making process (Bruinsma, Yang, Gill et al., 2016; Eck and Weisburd, 2015). This perspective makes it possible to improve the analysis of crime displacement and prevent crimes based on opportunity-reduction measures for specific areas more exposed to criminal activity (Cornish and Clarke, 1987). When applying the rational choice perspective to understand the offender's decision-making process towards committing violent crimes, it may also be possible to analyse what factors in the immediate environment influence or motivate the offender on where and when they engage in criminal activity (Bruinsma and Johnson, 2018; Cornish and Clarke, 2017). This understanding can provide valuable insights for law enforcement to develop effective crime prevention strategies (Cornish and Clarke, 1987). For example, if a series of armed robberies occur in a specific neighbourhood, it would be possible for the police to avert these robberies if they understand what attracts or generates crime in the respective area. Sometimes, the decision to commit robbery often begins with a desire or urge, and in some cases, this decision has been carefully planned (Feeney, 1986). Thus, the offender may choose a location and target based on reward, vulnerability, low security, and proximity to easily accessible escape routes. Also, if the specific crime is of more of an impulsive character, the same factors may trigger a potential offender (Cornish and Clarke, 2017). Therefore, by recognising the rational decision-making process behind the location, selection of targets, and the purpose of the crime, it can be possible to reduce tempting opportunities to commit a crime by manipulating the immediate environment (Sidebottom and Tilley, 2017).

Based on the findings of Weisburd and Piquero (2008 in Sidebottom and Tilley, 2017), rational choice theory could explain up to 78 per cent of the likelihood of committing a crime. Consequently, the notion of a *reasoning criminal* posits that background factors, previous experience, general needs, readiness, and the perceived solution to a problem might contribute to a theory that offenders are not simply irrational or impulsive but rather strategic and deliberate in their actions (Cornish and Clarke, 1986). Furthermore, whether the offender is impulsive or not, targets may be rationally selected by the offender (Braga and Clarke, 2014). Thus, implying there is a rational thought process before committing a crime, meaning crimes can be predicted or explained by the immediate environment and that it will be possible to reduce crime opportunities in a neighbourhood (Sidebottom and Tilley, 2017). For environmental criminologists and crime analysts, this could imply that the immediate environment may significantly influence where and when offenders choose to commit a crime. To further support the claim that the environment can influence criminal behaviour, Satz and Ferejohn (1994) challenge the psychology of rational choice and suggest that external factors are more likely to shape the agent's decision. Then, Satz and Ferejohn (1994) argue that with fewer environmental factors, human behaviour could be more challenging to predict using the rational choice theory.

Nevertheless, the rational choice theory is not without criticism. Although it was found that rational choice theory may explain a significant portion of the individual's motivation towards criminal behaviour, some scholars argue that the theory posits a limited predictive power and fail to capture the complete relationship between crime and rational decision-making (Boudon, 1998; Hechter and Kanazawa, 1997; Satz and Ferejohn, 1994). Explicitly, Hechter and Kanazawa (1997) argue that the rational choice perspective is unable to account for crucial factors such as personal values and cognitive abilities, which could play a significant role in shaping the individual's decision-making process. In some cases, a reasoning criminal may have *bounded rationality* and make shortcuts and simplifications purely motivated by the benefits of the crime, thereby neglecting potential risks. Bounded rationality implies that the offender is either unaware of the risks and consequences or thinks they have all the information they need to succeed (Carroll and Weaver, 1986). It also means that each offender possesses a unique basis for decision-making, considering the crime's underlying rationality, the individual's thought process, and the extent to which their rational choice selection is constrained. Similarly, research on offender mobility has demonstrated that offenders were attracted to areas with many potential targets and that the decision-making process on target selection exhibited bounded rationality (Braga and Clarke, 2014). Therefore, it is possible to argue that an offender's immediate environment can influence criminal behaviour due to calculations and other personal factors.

Moreover, the choice to commit a crime may appear reasonable and unreasonable, depending on the context and perspective. Consequently, the rational choice theory can be inadequate in fully explaining criminal behaviour. Satz and Ferejohn (1994) recognised that rational choice theory might be best understood by supplementing other theories. This thesis combines the rational choice theory with routine activity and crime pattern theories to address how these perspectives can influence offender decision-making and the formation of criminal patterns in time and space. Assuming routine activities contributes to form criminal patterns with the availability of suitable targets, and absence of capable guardians (Cohen and Felson, 1979; Hechter and Kanazawa, 1997), this theory may be effective in explaining the contextual rational decision-making when there is an opportunity for crime, when an agent's choices are limited (Satz and Ferejohn, 1994).

Routine activity theory

The routine activity theory, first introduced by Cohen and Felson (1979, in Miró, 2014), is an expanded and alternative criminological perspective to the cost-benefit analysis of crime from the rational choice perspective that focuses on changes in behaviour on a societal level to how the public's everyday movement patterns influence crime. Seemingly, daily routine activities and the behaviour of individuals combined with the different fundamental concepts of human ecology and social disorganisation are fundamental elements for understanding how individuals and offenders come together in time and space (Andresen, 2010). From a routine activity theoretical perspective, the motivated offender is, therefore, assumed to recognise opportunities for crime when encountering suitable targets during daily routine activities and when there is an absence of capable guardians (Felson, 1986; Felson, 1987; Kondo et al., 2018). Without any of these elements, a crime would be less likely to happen (Cohen and Felson, 1979). Similarly, Sherman et al. (1989) suggests in their study on hotspot activity and predatory crime that the magnitude of a crime depended on low guardianship or security where offenders could converge with vulnerable targets during their routine activities. Here, the absence of capable guardians can be considered a key factor in the occurrence of crimes (Felson, 1986; Felson, 1987), mainly because potential offenders are more likely to be deterred from committing a crime when the risk of being caught outweighs the potential benefits (Cohen and Felson, 1979; Felson and Boba, 2010; Miró, 2014).

On the other hand, the offender's state of mind may affect the motivation or rational thought process behind a crime. For example, violent criminal behaviour can increase in the vicinity of bars, likely due to alcohol consumption (Day, Breetzke, Kingham et al., 2012; Eck and Weisburd, 2015; Gerell et al., 2022). Contributing to violent behaviour in the vicinity of bars, Block and Block (1995) propose two mechanisms that can help explain the reason for increased crime in bar areas: the *psychological effect* of the increased risk-taking behaviour and the socially or culturally defined *disinhibition effect*. Firstly, the increased willingness to take risks (the psychological effect) could result in impulsive behaviour, fighting, vandalism or a greater likelihood of performing harmful activities. Secondly, alcohol consumption affects aggression and plays a significant role in developing violent behaviour (Rossow and Norström, 2012). In a situation with a temporary "time out" from everyday life followed by the social or cultural disinhibition effect, inappropriate behaviour is more likely to increase because the situation is defined as unserious or permissible to the offender. In contrast, this behaviour could be entirely out of line in another setting (Block and Block, 1995). Moreover, it was found that violent crimes also increased in close proximity to bars due to nearby opportunities and a lack of social control (Braga and Clarke, 2014; Felson and Clarke, 1998; Newton and Felson, 2015). According to the rational choice theory and routine activity theory, opportunities can be a central element for the offender's motivation to commit a crime (Felson, 2010). Consequently, crime might cluster in areas where the routine activities of offenders and targets intersect within a shared activity space. Although the mere presence of bars does not directly correlate to an increase in crime in a particular location, the movement of people attending routine activities, such as visiting a club with friends, can create opportunities for crime when the offender and target coincide in both time and space.

Building upon rational choice theory, the routine activity theory highlights how environmental and temporal factors can influence crime by focussing on crime patterns through a macro-perspective (Miró, 2014). Therefore, the routine activity theory may be applied to enhance the ability to comprehend and study the connection between everyday routines and crime in society. Through understanding the structure of the routine activity approach, Felson (2017) and Miró (2014) suggest that it can become possible to determine the frequency of crime and to predict where and when these crimes will be organised in society. The frequency of a crime in a specific area may be influenced not only by motives or capacity but also by the routines and behaviours of people (Felson, 2017). Some areas may be predominantly more vulnerable to criminal activity due to high flows of people and dynamics that can cause criminal events by concentrating at particular places (Braga and Clarke, 2014). Moreover, when offenders take advantage of the overlapping activity space between the three required elements in the crime triangle, they can find a way to commit a crime as it carves its niche into everyday life. Therefore, it can be necessary to understand how violent crimes are affected by various routine activities to prevent and predict future crime occurrences (Cohen and Felson, 1979). Felson (2017) explains that when using the routine activity theory to comprehend how routine activities affect predatory crimes, some essential points should first be understood. Firstly, most crimes can be considered routine as they develop from everyday routines and are subject to policy control. Secondly, offenders depend on convergence settings because crime shifts in time and space. Thirdly, some targets are more exposed to criminal activity because of their routines. For example, banks or jewellery stores may be at a higher risk of being robbed during routine activities, such as while handling large amounts of money on the premises. Finally, analysing routine activities and crime patterns has led to other practical developments within environmental criminology, including problem-oriented policing and predictive policing.

Previous research in the field of environmental criminology has considered routine activity theory to be an integral part of describing predatory criminal events as an opportunistic process where the offender and target come together in time and space (Anselin et al., 2000; Felson and Clarke, 1998; Kondo et al., 2018; Ratcliffe, 2006). Routine activities can systematically create criminal opportunities for potential offenders by providing a predictable pattern of targets that can be easily observed (Santos, 2017). By taking into account Cornish and Clarke's (1986) concept of a reasoning criminal, which suggests that offenders are rational and deliberate in their decision-making, along with Felson's (1987) argument that offenders employ lazy reasoning, it can be inferred that some offenders select targets based on minimal effort and criminal opportunities connected to routine activities. As a result, the offender may overlook more profitable targets located off-route (Felson, 1987). Felson (1987) suggests that in similar cases, the offender also employ the principle of *the most obvious*, meaning that offenders take quick risks and expose themselves for a brief time rather than awaiting better opportunities. From a broader perspective, the offender's decision-making process might be bounded by the availability and presence of potential targets, influenced by impulsiveness or laziness and a lack of awareness that a greater effort could lead to more rewarding opportunities (Felson, 1987).

Therefore, it is possible that searching for different patterns and movements connected to offenders, crimes, and routine activities can be used to understand where and when crimes have an increased likelihood of being committed (Kaufmann et al., 2019).

Crime pattern theory

Sometimes crime patterns and trends can be obvious; other times, they are discernible only through insight embedded within the environment (Brantingham and Brantingham, 2008). Crime pattern theory emerged as the *geometry of crime* from the work of Paul and Patricia Brantingham (1993a; 2017), who studied crime patterns through the lens of city structure. Crime pattern theory is a combination of routine activity and rational choice theory, and suggests that identifying, and analysing, everyday movement patterns can be fundamental for developing effective policing strategies to anticipate, prevent and respond to crime in society (Pearsall, 2010). More specifically, crime pattern theory can explain what connects suitable targets and motivated offenders by observing routine activities, opportunities for crime, and looking at daily movement and activity nodes (Brantingham et al., 2017; Townsley, 2017). Crime pattern theory can be seen as the epistemological core of environmental criminology because it has been used to further explore the offender's adaption to place and the intricate relationship between offenders, *crime attractors*, and *crime generators* (Brantingham and Brantingham, 2008; Kaufmann et al., 2019). For this reason, crime pattern theory can provide a structured framework for crime analysts to investigate and comprehend criminal events (Santos, 2017).

Albeit what attracts and generates crime can shift in time and space, Brantingham et al. (2017) explain that movements of people in proximity to nodal activity points can contribute to generating or attracting crime, primarily when targets are located in areas where individuals may have a greater willingness to commit a crime. Crime generator areas can be defined as locations that attract individuals who do not necessarily have criminal intentions but can generate crime based on the available opportunities (Brantingham et al., 2017; Malleson and Andresen, 2016). Some people in a particular place and time can create an environment that facilitates offending, thereby generating more crimes in the area (Brantingham et al., 2017). Here, typical crime facilitators or generators can be shopping malls, transit stations and other areas that attract a large flow of people (Braga and Clarke, 2014).

Conversely, Brantingham et al. (2017) and Braga and Clarke (2014) explain crime attractor areas as places well-known for criminal opportunities to which intending offenders are attracted. In this case, potential offenders can, for example, be attracted to bar districts, drug markets, public transit areas or large shopping centres where committing a violent crime may be a more frequent activity. From the geometry of crime perspective, the *environmental backcloth* is used to comprehend crime opportunities with contextual rationality, encompassing the social, political, economic, and physical dimensions of how individuals navigate their surroundings (Brantingham et al., 2017). The concept of the environmental backcloth, first introduced by Brantingham and Brantingham (1993b), aims to explain people's activity and movement within and through space and how this backcloth impacts all activities, both criminal and non-criminal. The environmental backcloth considers an area's complex social, physical, and cultural features and explains how these features may increase the potential for criminal hotspots (Deryol et al., 2016). By comprehending the nature of the environmental backcloth when considering violent crime patterns, it can become possible to predict where and when violent crimes are more likely to happen (Brantingham et al., 2017).

Furthermore, Brantingham and Brantingham (2008) established that nodes and paths in the area where a potential offender contemplates committing a crime could be known as the *activity space*, and areas typically within the offender's visual range of the activity space are called the *awareness space*. According to some scholars, crimes were more likely to cluster near the offender's activity and awareness space and concentrate near activity nodes where the offender requires specific factors to be present (Brantingham et al., 2017; Ratcliffe, 2012; Townsley, 2017). Here, crime events can become a circular process. First, the potential offender requires a situation or place where they can perform criminal activity. Subsequently, the potential offender's state of readiness for committing a crime can operate as a motivational trigger along with the spatial awareness and activity space influenced by the commission of the crime. The potential offender may then assess the quality of the place and the characteristics of the targets, which may generate further motivation to commit a crime (Brantingham and Brantingham, 2008).

Similarly, networks and routine activities are subject to change, which can lead to modifications in the offender's activity and awareness space (Brantingham et al., 2017). As an illustration, Brantingham et al. (2017) found that criminal activities may become concentrated in regions where activity spaces overlap with routine activities, attracting individuals from other parts of the community whose awareness spaces intersect with the area and designating it as an activity node. Going back to Zipf's principle of least effort (1950 in Felson, 1987), criminals will be more likely to commit their initial crimes near nodes or paths between their different routine activities or near the paths and activity nodes of their friendships network (Brantingham and Brantingham, 2008). Suppose a crime opportunity arises outside of their usual area. In that case, the offender may start casing the new location to familiarise themselves with the routines and behaviour of those in that area (Santos, 2017). This argument contrasts Felson's (1987) notion of lazy reasoning criminal because the potential offender will move outside and away from a familiar space, suggesting that offenders can make rational choices. On that note, Brantingham et al. (2017) suggest that offenders travel longer if there is an area where intending offenders know they can commit a crime with fewer risks attached. For this reason, understanding the actual patterning of crime can make it possible for law enforcement to identify crime hotspots and for policymakers to implement effective crime prevention strategies that more efficiently can reduce the risk of criminal activity (Brantingham et al., 2017; Brantingham and Brantingham, 1993b; Ratcliffe, 2006; Townsley, 2017). Similarly, with constantly improving data analysis technology, methods of predictive policing can contribute to improved police work by preventing crimes before they happen and responding more effectively to crimes when they do (Pearsall, 2010; Ratcliffe, 2006).

Temporal constraint theory

While environmental criminologists focus most of their research on the spatial distribution of crime, they often acknowledge that it is equally critical to consider the *temporal interdependence* and *constraints* of crime rates (Cohen and Felson, 1979; Ratcliffe, 2006). This acknowledgement can be necessary because neither crime opportunities nor motivated offenders are uniformly distributed in space and time (Brantingham and Brantingham, 1993a; Newton and Felson, 2015; Ratcliffe, 2006). Both the location of targets and potential offenders travel with a regular movement pattern which usually varies depending on time, characteristics of targets and what situations surround the targets (Ratcliffe, 2006). Mapping the temporal patterns of specific crimes could, therefore, be crucial for detecting spatial change over time (Xia et al., 2021). Close parallels between offender decision-making, routine activities and both spatial and temporal constraints can cause some offenders to commit a crime where they will not arouse suspicion by blending into the ambient population (Townsley, 2017). As previously mentioned, violent crimes might be associated with nightlife, where large crowds can force a constrained movement pattern. Gerell et al. (2022) conducted a study which revealed an association between the opening times of bars and the occurrence of violent crimes in Oslo. Their study found that when reducing the opening or closing times of bars altogether, it appeared to be a reduction in violent crimes. These findings suggest that potential offenders contemplating committing a violent crime are drawn towards crowded areas that enable the offender to blend into the ambient population more easily after committing a violent crime. More specifically, in crowded areas, the offender and target converge in space or time, where capable guardians may not have clear visibility and may be unable to intervene. This completes the crime triangle, increasing the likelihood of a violent crime.

Furthermore, Newton and Felson (2015) argue that the analysis of violent crime patterns relies on indicating both the temporal and spatial distribution to identify crimes. When it comes to violent crimes, in particular, previous research suggests that they are more likely to happen in the evening (Almanie et al., 2015; Brantingham and Brantingham, 1993a; Uittenbogaard and Ceccato, 2014). When looking at seasonal patterns, crimes were more likely to increase in summer (Ratcliffe, 2010). These findings are further reinforced by Almanie et al. (2015), who found that violent- and drug crimes in Los Angeles and Denver were more likely to cluster on Wednesdays and in the four hours before and after midnight at the weekends (Friday to Sunday). When exploring routine activities and the implications of temporal constraints, Ratcliffe (2006) suggests that the motivated offender's temporal constraints can be imposed by the need to be in a place at a specific time. Henceforth, to understand and acknowledge the importance of temporal factors and patterns, as well as detect the spatial change in violent crimes, it can be necessary to address and identify the underlying causes of the crime to design effective prevention strategies (Weisburd, 2015; Xia et al., 2021). This argument is further supported by Ratcliffe (2010) and Newton and Felson (2015), who contend that knowing the temporal trends of violent crimes can aid in the allocation of resources and the development of preventative measures to ensure public safety during the time the crime rate is increased.

The effect of weather on crime

Although the impact of weather on crime can be significant, there have been few empirical investigations into how weather affects the location of crimes (Hart et al., 2019). Researchers studying crime in Sweden postulated that seasonal changes could influence routine activities (Uittenbogaard and Ceccato, 2014). This observation prompted Uittenbogaard and Ceccato

(2014) to explore the possibility that changes in weather patterns may also affect crime patterns. Assuming that the effect of weather could increase crime, this would fit well with the expectations of routine activity, rational choice, and crime pattern theory because the offenders' and targets' activity and awareness space would be more likely to overlap when the movement of people increased (Hart et al., 2019). Furthermore, when the effect of weather on crime was measured on a 30-year panel of monthly crimes in the United States, it was found that temperature had a strong positive effect on criminal behaviour and that violent behaviour would increase as the temperature rose (Ranson, 2014). Nevertheless, Hart et al. (2019) concluded that weather conditions in Norway had little to no importance for practical policing since the effects on crime intensity were microscopic and had an even more negligible effect when measuring how the weather could affect crime locations. Therefore, they contend that relying solely on weather forecasts would not be adequate for predicting crime in Oslo. To accommodate Hart et al. (2019) recommendation that weather should not be used individually when attempting to predict violent crimes in Oslo, this thesis will examine the impact of weather (including temperature, wind, and rain) as an additional feature in the crime prediction alongside other environmental and temporal factors.

Crime prevention through environmental design

Consistent with crime pattern theory, violent crimes occasionally cluster at the endpoints of the pathways that connect routine activities and nodal areas (Brantingham et al., 2017), which could explain why some parts of a city never experience crimes while others are more or less persistently exposed to criminal activities. Potential offenders and suitable targets often interact in specific spatial settings or locations where crime clusters, according to research by Bruinsma and Johnson (2018). These criminogenic settings may include proximity to bars, highways, buildings (business or residence), transit stops, and other places where there could be an easy escape route or a mix of drugs and alcohol (Anselin et al., 2000; Block and Block, 1995; Eck and Weisburd, 2015; Ferguson, 2017). Correspondingly, crime may cluster along the path to activity places close to nodes and act as crime attractors or crime generators for these nodes (Brantingham et al., 2017; Deryol et al., 2016). In other words, places where criminogenic factors are present can contain particular geographic vulnerabilities that can allow for crime prediction (Ferguson, 2017). Thus, altering the physical environment in which crime events happen, or being aware of crime patterns tied to criminogenic factors, can make crime control possible (Jeffery, 1969; Jeffery, 1976). For example, if two people fight in a bar, the police must investigate what within the environmental space can contribute to causing violent behaviour (Felson and Boba, 2010).

Moreover, with the advancement of spatial crime research, it is now feasible to analyse the direct impact of land use on the location of crimes and its broader spatial influence on the surrounding area (Hipp and Williams, 2020; Ratcliffe, 2012). Considering this development, understanding the criminogenic factors that can influence violent crimes may be fundamental for enhancing policies targeted at crime prevention. Thus, locating and analysing these factors could help law enforcement allocate resources to address violent crimes in society and further investigate, control, and reduce the prevalence of crime in these areas (Wortley and Townsley, 2017). It was argued by Jeffery (1969) that it was possible to learn a great deal about crime by studying the relationship between the environment and criminal events. Something unlikely to be achieved by studying single crime events. For instance, if assaults or other forms of violent criminal behaviour frequently occur in a place, it may be imperative to investigate the geographic context in which the bar is situated rather than analysing these incidents in isolation. Here, crime patterns can function as a universal driver for predictive analysis because the data can be identified and may show regularity over time (Kaufmann et al., 2019). Nevertheless, discovering that many violent crimes are located close to a specific area does not necessarily mean that criminogenic factors attracting violent crimes in this area are generalisable for similar locations (Hipp and Williams, 2020; Jeffery, 1976). This lack of generalisability can be attributed to the underlying criminogenic factors unique to a spatial or temporal setting, which could help explain the concentration of violent crime incidents at a particular location (Townsley, 2017). Distinct features or circumstances of a location can, therefore, indicate that the analysis may not be generalisable to other environments or categories of crime. At the same time, it can provide some direction for future research on similar situations.

Furthermore, a crime prediction study by Alves et al. (2018) found that violent crimes can depend heavily on urban indicators. Most likely because cities often share similar components, such as their urban development, street networks, travel paths, transit routes and the land use that shape the city’s structure (Brantingham et al., 2017). As a result, these paths, networks, and land use may be constructed to facilitate a specific movement pattern that can constrain people within an area. This construction may suggest that the physical layout of an area can help explain why criminals encounter potential targets between major routine activity nodes or along their usual travel paths (Brantingham and Brantingham, 1993b). It can also contribute to analysing the specific movement pattern of potential offenders in a city and how the impact of underlying road structures can provide information on where crime attractors and generators are situated (Brantingham et al., 2017). If this is true, then it is likely that the placement of activity nodes might determine which areas may be more exposed to criminal activity. Subsequently, performing spatial crime analysis to understand the physical aspects of crime prevention and predictive policing can enable law enforcement and policymakers to implement new policies targeted at reducing crime close to these activity nodes, as well as strategies that can reduce crime through environmental design (Brantingham et al., 2017; Felson and Boba, 2010).

Crime prediction with machine learning

While crimes are determined by various factors that cannot always be quantified, statistical modelling of violent crimes may allow researchers to simulate crime hotspots and analyse different dynamical patterns. Implementing a quantitative approach to measuring violent crime in Oslo can help to identify practical solutions for reducing crime in particular areas throughout the city. Nonetheless, crime prediction using statistical models is generally challenging if crime data is sparse[4] in time and place since this can lead to uncertainty in predictions and other calculations (Wang et al., 2019). However, supervised machine learning can provide valuable information through a remarkably accurate prediction system (Berk and Bleich, 2013). More explicitly, such machine learning-based forecasting models can contribute to predictive policing by precisely predicting criminal involvement, behaviour, and locations (Oh et al., 2021). In previous research, linear regression models, including logistic regression, appears to be the favoured statistical tools for crime and risk forecasting (Berk and Bleich, 2013; Deryol et al., 2016; Kounadi et al., 2020; Thomas and Drawve, 2018). Here, the regression's fitted values determine the probabilities or the linear relationship between the predictors and crime dependent. The random forest model is non-linear and tends to score higher in predictability than similar models, which could imply that this is one of the better models to use for predictive policing (Mohler and Porter, 2018; Wheeler and Steenbeek, 2021; Zhang et al., 2020). Therefore, performing crime prediction through machine learning, in this case, a random forest algorithm, may help bridge the scientific research gap between predictive policing and social science by implementing a more statistically advanced model with higher prediction accuracy.

[4] Scattered with no obvious patterns.

Unlike regression analysis, the random forest model is unable to identify significant correlations between crime and different variables. Nonetheless, the non-linear nature of the random forest model allows it to score higher in predictability than simpler models, making it a valuable tool for predictive policing and identifying areas more susceptible to future criminal activity.

Crime mapping, facilitated by machine learning, offers valuable insights for understanding the interplay between geography and opportunity and can help identify spatial patterns, which can further inform the development of targeted crime prevention strategies for specific locations (Ratcliffe, 2010). Berk (2013) argues for a necessary shift in attitudes among criminologists to embrace an algorithmic perspective, highlighting the complexity and unknowable nature of the data produced within a machine learning algorithm. Sometimes, the intelligibility of a machine learning process can suffer from a so-called *black box* problem[5] (Chan, 2021). This complexity may discourage scholars from using advanced learning-based algorithms for predictive policing because it can be challenging to comprehend, implement, and interpret, even for experts (Berk, 2013; Chan, 2021). Thus, it may be challenging to locate research in criminology that applies advanced AI-based technology (Berk, 2013). In some cases, the black box of machine learning, or how an algorithm teaches itself to improve, might not be understandable from a human perspective (Cohen and Graver, 2021). Due to the unintelligibility of black box machine learning systems, even to computer scientists, individuals may be reluctant to use more advanced techniques and technologies for predictive policing out of the fear that they are unable to challenge possible system errors or of being held accountable for decisions made as a result of the model's output (Mcdaniel and Pease, 2021a). Furthermore, Mcdaniel and Pease (2021a) argue that it is fundamental for the police to comprehend the technology they use when applying it to a real-world setting. Consequently, over-reliance on inadequately understood, evaluated, or accepted technologies can result in miscarriages of justice, even for individuals with rudimentary experience of police history.

---

[5] The black box problem encompasses the challenge of comprehending the inner workings of a computer's decision-making process. Castelvecchi (2016) draws a parallel between machine learning and neuroscience, emphasising the reliance on cognitive processes despite lacking a complete understanding of brain functioning. See Castelvecchi D (2016) Can We Open the Black Box of Ai? *Nature* 538(7623): 20–23. 10.1038/538020a

The implications of crime mapping in the real world

The preceding sections have attempted to demonstrate how crime mapping and crime forecasting can provide insightful knowledge to predictive policing policies and why this method could be applied to address crime in urban areas. Recognising that no theory or practice is flawless, the following section briefly considers some implications of crime mapping and common difficulties crime analysts may encounter when mapping crime in urban areas. Furthermore, predictive policing may raise ethical and moral implications that should be further discussed.

A confirmation feedback loop in predictive policing

The abovementioned theoretical framework suggests that social control may reduce violent crime opportunities without officers directly approaching potential offenders (Brantingham et al., 2018). Equivalently, the physical presence of police, or visible guardians, can increase social control by deterring potential offenders from committing violent crimes. However, when the police enter the area where a crime was predicted, they also affect what happens in that place which can create a paradox (Shapiro, 2021). When using predictive policing technologies to forecast and prevent crime, it can generate a feedback loop where biased data triggers increased policing of specific areas where the police frequently return due to increased crime rates. More specifically, these cycles of policing can trigger a confirmation feedback loop when biased and concealed patterns guide police action towards specific areas where they encounter expected criminal activity (Kaufmann et al., 2019). This self-fulfilling prophecy can result in over-policing, leading to *territorial stigmatisation*, where geographical areas, or neighbourhoods, based on their association with crime, low socioeconomic status, or other undesirable characteristics are further stigmatised and marginalised (Wacquant, Slater and Pereira, 2014).

Clavell (2018) contends that the risk of utilising disproportionate, or biased, data carries the potential for territorial stigmatisation and unjustified profiling based on ethnic, socioeconomic, or religious characteristics. Deploying officers based on biased crime statistics can lead to over-policing and additional discrimination against, or biased apprehensions of, minorities or individuals associated with perceived high-risk areas that the police are encouraged to patrol, something that may remove the possibility for officers to reflect on what they see (Brantingham et al., 2018; Kaufmann et al., 2019; Richardson et al., 2019). This lack of reflection can result in increased stop and search interferences, leading to random and arbitrary stops, targeting individuals who are perceived as suspicious or potentially involved in criminal activity (Mcdaniel and Pease, 2021a). Increased stop and search interventions can lead to unfair targeting and disproportionality in the data by criminalising individuals of a stigmatised "suspect population" (Newburn, 2011). This fosters the confirmation feedback loop because more offences are registered in these areas, causing the police to repeatedly return to the exact location regardless of the actual crime rate (Richardson et al., 2019).

"Fairness" in predictive policing

If crimes have been found to concentrate on a specific time and place (Kondo et al., 2018; Malleson and Andresen, 2016), then the goal might be to send police resources to areas where an increase in crime events is predicted, whether spatial or temporal, to be able to reduce crime in that specific area. At the same time, law enforcement and policymakers should consider the distribution of criminal behaviour to avoid over-policing regions predicted to be more exposed to crime (Araújo et al., 2018). Failure to mitigate over-policing in high-risk areas can lead to adopting a more proactive policing approach in regions with criminogenic cues because it can be perceived as an effective crime prevention strategy (Mcdaniel and Pease, 2021b). The consequences of this proactive approach can inadvertently create a self-fulfilling prophecy where an increased focus on people or areas may result in a rise in stop and search interventions, leading to biased arrests and the unfair targeting of specific neighbourhoods or individuals (Brantingham et al., 2018). According to Newburn (2011), the self-fulfilling prophecy or feedback loop in predictive policing may perpetuate a cycle of bias that can contribute to social inequalities within the criminal justice system. Additionally, it is possible that increased targeting of individuals increases the apprehension rate, while crime rates are not genuinely reduced or mitigated (Chan, 2021). As a result, using predictive policing to address crimes due to biased and unfair policing practices may disproportionately impact marginalised communities, as they are subject to higher levels of police surveillance and discrimination (Hamilton, 2021).

Even though intelligence-led recommendations can be necessary for supporting decision-making, it is essential that predictive policing through AI-based models are used with caution since a computer might be unable to dispute professional judgement (Richardson et al., 2019; Selten, Robeer and Grimmelikhuijsen, 2023). While crime mapping facilitated by machine learning may appear to offer objectivity, accuracy, and efficiency, the enforcement of criminal justice may still suffer from inherent unfairness due to the over- or underrepresentation of a specific group or place (Chan, 2021; Mcdaniel and Pease, 2021b). Thus, systematic biases in the data can result in unfair predictions, targeting or discrimination against a group or area, resulting in biased predictions for where and when officers should be deployed (Chan, 2021). Consequently, Clavell (2018) contends that the neutrality of the data depends on the knowledge and expertise of those who gathers and analyses it.

If the individuals responsible for data analysis have a limited understanding of result interpretation, there is a risk of drawing biased conclusions influenced by their subjective opinions (Clavell, 2018). Furthermore, Chen (2021) suggests that a solution to a biased prediction can be to ensure the system does not result in a confirmation feedback loop by testing and refining its performance, continually regulating its outcomes, and implementing mechanisms to handle systemic errors. Similarly, Clavell (2018) and Selten et al. (2023) argue that it is essential to bear in mind the cultural and social complexity of the environment where predictive policing technology will be applied and that human-computer interaction is especially worrisome if police officers are more likely to ignore visible biases in the model when it aligns with personal judgement. Failure to address systemic bias can lead to racial profiling, perpetuating existing inequalities, and reduce public trust in law enforcement due to increased targeting through stop and search interventions, ultimately compromising community safety (Solhjell, 2019). Conversely, Selten et al. (2023) contend it is possible to de-bias the AI model if the data is carefully gathered, tested, validated and modelled. Therefore, knowledge and transparency are essential when incorporating AI technology for predictive policing. It may also be important that the police continue to use human discretion to correct bias in the technology (Selten et al., 2023). In summary, practices based on predictive policing technology should ensure transparency and fair assessments without perpetuating existing biases.

Methodology

The following section of this thesis provides an overview of the statistical methods applied to perform a random forest analysis to predict violent crimes in Oslo with GIS. This study draws on data from the Norwegian criminal register (STRASAK), map data with various shapefiles from Open Street Map (OSM), and weather data from the meteorological institute (MET). This section outlines the study setting, methodology, and data preparation process. Additionally, this section includes a discussion of ethical considerations for performing the data analysis. The expectations for this study were to achieve the research objective by determining whether spatial analysis through machine learning could serve as an effective tool for predictive policing.

With a growing recognition of quantitative research, statistical learning can be a powerful tool for understanding the interplay between crime and its distribution through space and time (James, Witten, Hastie et al., 2013). More specifically, quantitative research methods can describe patterns, origins, and responses to crimes and criminal activities, it can also generate essential descriptive information fundamental to many public policies and criminological theories (Piquero and Weisburd, 2010). Researchers have long discussed the value of mapping spatial crime patterns and have proposed a variety of techniques and approaches for doing such an analysis (Ignatans and Pease, 2008; Jung, Patnam and Ther-Martirosyan, 1993; Murray, Mcguffog, Western et al., 2001; Wang et al., 2019). Specifically, crime mapping using GIS and supervised machine learning models, such as random forest, have been found to provide the most accurate representation and prediction of where crime is, or will be, located within an area (Alves et al., 2018; Berk, 2010; Oh et al., 2021).

As mentioned, this thesis aims to analyse the spatial and temporal aggregation of violent crimes within Oslo through GIS and random forest. More specifically, the aim is to predict where violent crimes will happen in Oslo and examine how learning-based algorithms can contribute to predictive policing. While larger cities such as Chicago, New Jersey, Vancouver and Los Angeles have been extensively studied within the field of environmental criminology (Andresen and Malleson, 2011; Anselin et al., 2000; Caplan, Kennedy and Piza, 2013; Ferguson, 2017; Wang et al., 2019), Norway's relatively small population positions it as a minor country by comparison (Ssb, 2022a). Despite being the capital of Norway, Oslo with a total area of 454 km^2, 707 531 residents, and 189 651 commuters (Ssb, 2022b), makes it a city of lesser scale in the context of environmental criminology. Thus, Oslo presents a unique case study for understanding violent crime patterns and developing effective crime prevention strategies. Given Oslo's geographical size and population, this study could be considered a meso-level analysis. In a geographical research context, meso-level analysis refers to the study of smaller cities or districts within a metropolis, ranging from suburbs to individual street segments (Brantingham and Brantingham, 1991 in Wortley and Townsley, 2017). This analysis examines the overall violent crime distribution and trends in Oslo from 2016 to 2020, and the different micro-geographical units of analysis will be explained in detail below.

A map of Oslo

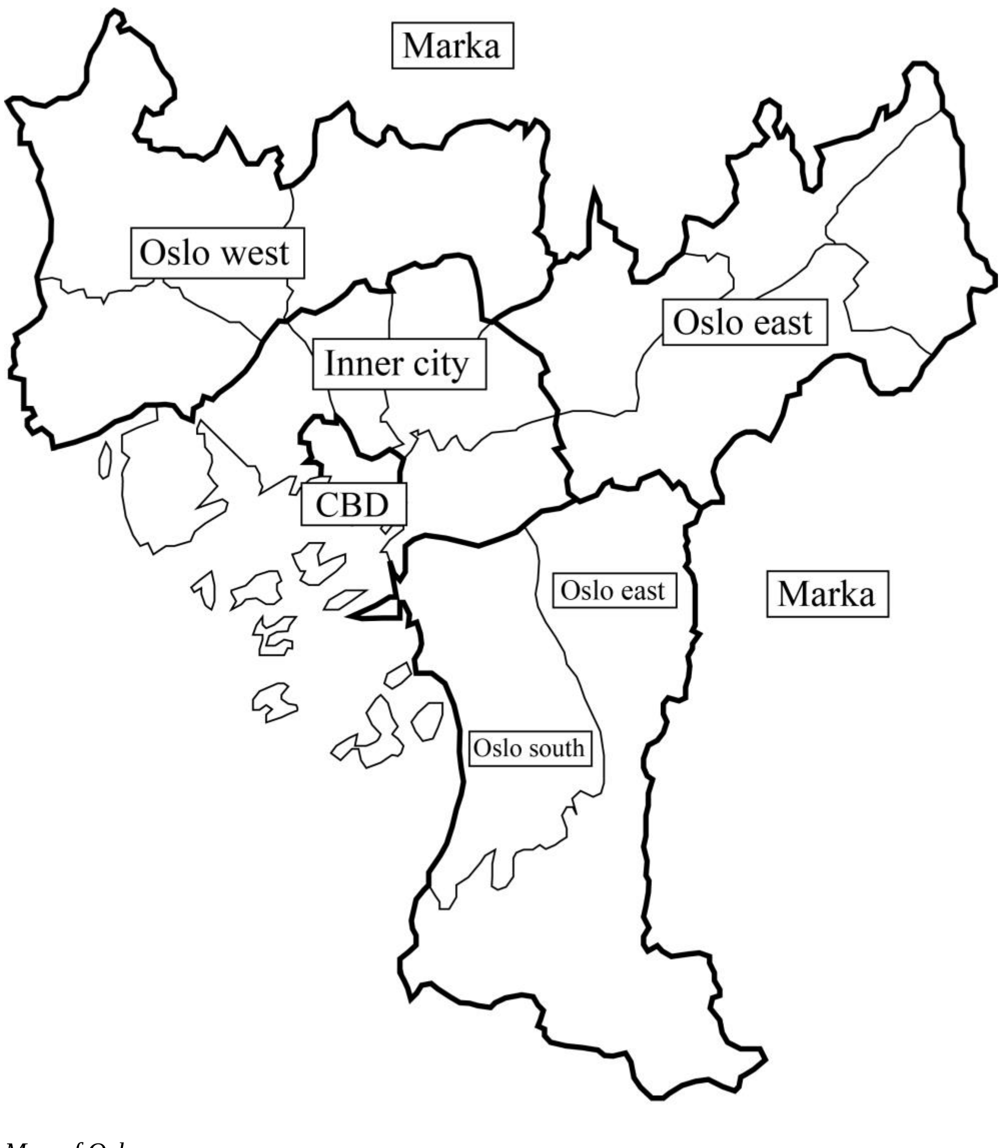

Figure 1: Map of Oslo

Figure 1 displays a map that intends to show the geographical location of Oslo and to provide context for any possible socioeconomic inequalities that could contribute to variations in the violent crime distribution across the city. Oslo's geographical region splits into five zones, including the inner city, the city centre (also known as Central Business District or CBD. See Figure 1), two outer zones: West and East, and Marka which primarily consists of a nature area. Within the CBD, the city's main central station connects other public transport nodes and serves as a central nodal point expected to generate high traffic volumes (Tennøy, Øksenholt and Aarhaug, 2014). In the context of this thesis, it is predicted that the eastern part of Oslo has a higher incidence of violent offences compared to the western part. These differences in crime patterns may be influenced by the various factors specific to each area. Therefore, to understand the violent crime distribution in Oslo, it may be necessary to comprehend how the different regions in Oslo can contribute to crime in separate ways. In the eastern or downtown areas of Oslo, there are many Norwegian citizens born with an immigrant background who has been found to start their criminal careers at an early age (Glomseth and Aarset, 2022). Glomseth and Aarset (2022) argued that a proportion of the young offenders in Oslo come from disadvantaged backgrounds, with broken families and early exposure to crime. These offenders often reside in areas characterised by socioeconomic differences from the rest of Oslo's population (Wessel, Turner and Nordvik, 2018). Furthermore, it was found in a study conducted on young offenders in Oslo that the western part of the city experienced more drug-related offences, while the eastern part had a higher incidence of violent offences (Bakken, 2018). Bakken (2018) suggests high incidents of crime differences are related to social inequalities and socioeconomic statuses.

Geographic Information Systems (GIS)

Ratcliffe (2010) states that crime data with spatial and temporal information should be computerised and analysed using appropriate software. In this context, GIS and machine learning can be practical tools for processing, managing, and disseminating geographical data (Ye, Brown and Harding, 2014). GIS can be an especially appropriate method for crime mapping because of the possibility to store spatial information as *points* indicating the locations of crime events, *lines* depicting, for example, street networks, or *polygons* for administrative areas, parks, or to protect people's privacy by storing areal information or demographic data on an aggregated level. GIS is capable of handling raster (grid) data for aggregation purposes, which reduces the risk of identification of crime offenders or targets.

To be able to implement new policies and recommendations for predictive policing based on crime data, accurate georeferencing of where a crime event happened is fundamental. Albeit the X and Y coordinates representing the geocoded location are typically assumed to be as geographically accurate as possible, this assumption cannot be taken for granted in the context of spatial crime data. This is because the reliability of the registered addresses can be uncertain, leading to potential registration mistakes. Some registration mistakes can be managed using grid cells at different spatial levels and considering the spatial dependency. For this thesis, a raster map with 100x100 meters, 250x250 meters, and 500x500 meters grid cells were created, and a classification scheme was implemented for assigning features to their corresponding grid. A feature was allocated a value of 0 if absent from the grid and 1 if present in the grid. The geocoding of the data used in this research surpassed the minimum acceptable geocode hit rate of 85 per cent (Ratcliffe, 2004).

With improved analytical techniques and data availability, applying GIS and machine learning technology for crime mapping can contribute to predictive policing and crime prevention with new opportunities to explore crime patterns and high-risk areas (Ratcliffe, 2004). Using GIS enabled connecting geographical data with crime data and other factors that might influence violent crimes. The data was cleaned and processed before running the spatial and temporal prediction algorithm.

Datasets and data collection

This thesis is connected to an ongoing project[6] at the Norwegian Police University College that utilises data from the Oslo Police District's (STRASAK) crime registry, which includes detailed information about all criminal offences reported during 2000-2020, including time, date, and geographical coordinates. The STRASAK crime registry includes key characteristics of reported crimes and police criminal proceedings, as well as their progress over the years (Politiet, n.d.). For instance, this registry includes data on a personal level, an overview of reported offences and the major outcomes for the police's criminal case processing, including the number of prosecution decisions, case duration, clearance percentage and much more. These

[6] Project "Mapping and forecasting crime in smaller cities; relevance for Norwegian research and policing". More information on this can be found in the section under *Ethical Considerations.*

are all separated into different crime categories, as determined by Statistics Norway (SSB)[7]. However, due to ethical considerations (which will be further discussed), the data for this thesis only includes a subset of the original STRASAK data. This subset explicitly includes time- and place-specific information about the crime events and type of crime. In some areas, this information could involve a risk of indirect exposure of people who may have been involved in cases on a small scale. More explicitly, the risk of identification only applies when processing the data material, and it will not be possible to identify any persons when results from the analyses are extracted from the processing area or when publishing. Consequently, this thesis is explicitly interested in mapping patterns and trends of violent crimes and will not discuss anything related to crime on an individual level or any interactions with the legal system.

The original STRASAK data contain longitude (X) and latitude (Y) coordinates for the specific crime location, which can be used to map and forecast crimes in the machine learning model. Some observations had missing coordinates, but many addresses could be received from a free text field for most cases. Therefore, the data for this project were geocoded and adjusted to the correct local coordinate system by my supervisor. During this process, some observations were excluded due to missing coordinates and addresses or inaccuracy in the geocoding process that could lead to uncertainty[8].

Similarly, after restricting the data[9] from 1st January 2016 to 31st December 2020, the subset of data on violent crimes used in this project consists of 34408 observations. More specifically, the group of crimes are based on the standard classifications of violence and maltreatment established by SSB. These violent crimes include bodily harm, assaults, robbery, extortion, coercion, deprivation of liberty, human trafficking, terror-related offences, and miscellaneous types of violence or maltreatment (Stene, 2017). It is necessary to point out that there are

---

[7] Information on the classification of crime types, post the penal legislation act 2015, can be found here: https://www.ssb.no/en/klass/klassifikasjoner/146/koder

[8] For example, in some cases, only "Oslo, Norway" was entered into the system address field by the police. This practice is performed both when a more specific address is unknown or if the violent crime happened on a train or other public transport where the end station is Oslo. The coordinates for "Oslo, Norway" are a location on a street segment in the central area a bit north of the central station. Including these crimes will overestimate the number within one of the grid cells, and they are therefore excluded from this thesis.

[9] After the revised penal legislation in 2015, some crime data collected after this date has received a new definition and been replaced with separate categories for the offences. Therefore, integrating data from before and after 2015 in this project may result in complications due to variations in the definitions of what qualifies as violent crimes. See Jacobsen J and Sandvik VH (2015) An Outline of the New Norwegian Criminal Code. *Bergen Journal of Criminal Law and Criminal Justice* 3(2): 162-183.

specific types of violent crimes that involve offences within family relations and similar context. However, it is crucial to clarify that sexual offences, being distinct violent crimes, are not included in this dataset and requires separate analysis and consideration. Furthermore, to increase the likelihood of achieving the target analysis of this research, the time and date observations have been sorted into 52 weeks in each year from 2016 to 2020, making the data handling process easier (Nguyen, Hatua and Sung, 2017). Since the data is longitudinal, it can provide an empirical foundation for the data analysis of developmental trajectories that are fundamental to the social sciences (Nagin, 2010). By describing the progression of violent crimes in an area and identifying the variables that correlate with specific changes, developmental trajectories can provide valuable insights for crime prevention and policymaking.

Moreover, to relate the data to the findings discussed in the literature review, data from OSM and MET were also included in the final analysis[10]. Based on the literature review findings, a city's environmental structure and various spatial features can be crucial for creating a criminogenic environment. Therefore, the data from OSM contains various shapefiles with information on various spatial features added onto the geocoded data and Oslo map. The Oslo map was split into 100x100m, 250x250m, and 500x500m grid cells to examine how the model's accuracy differed with various sizes. Splitting the map into grid cells enabled the random forest model to predict crimes in these grids. The model could also identify features that may or may not increase violent criminal activity. Furthermore, the OSM data provides public transit networks, public pathways and areas, road structures, as well as information on residential and non-residential buildings in the city. For this reason, these crime prediction models may be able to connect different routine activities and their location to violent crimes and be able to provide necessary information for predictive policing about where and when a violent crime happened and what can be done to prevent the area from further criminalisation. Additionally, data from MET has been included in this analysis since it was found in a Swedish underground study that crime was dependent on seasonal trends (Uittenbogaard and Ceccato, 2014). More specifically, Uittenbogaard and Ceccato (2014) posited that in a Scandinavian context, the extreme temperature and seasonal changes were bound to impact crimes due to the weather's influence on people's routine activities. Therefore, it would be interesting to research if this also applied

[10] A complete list of all variables included in this analysis can be found in the Appendix 1.

to the Norwegian context despite Hart et al. (2019) argument that weather-specific surfaces had no importance for crime prediction when using a generalised additive model.

Data pre-processing

I performed necessary data pre-processing steps to assess the data quality and ensure that the data had been properly handled for the random forest model. Pre-processing, also known as data preparation, is essential for enhancing data quality and preparing for data mining to achieve accurate results and contribute to knowledge discovery (Babakura, Sulaiman and Yusuf, 2014). The main objective of pre-processing is to structure and organise the data by constructing a framework for applied predictive modelling and to improve the subsequent classification model for future yet-to-be-seen data (Kuhn and Johnson, 2019; Rinnan, Berg and Engelsen, 2009). To ensure the data was suitable for the crime analysis, the following pre-processing steps encompass a series of procedures, including data cleaning, integration, feature engineering, and selection (Babakura et al., 2014).

Data cleaning

To clean the data, I selected the most relevant attributes from the subset of the STRASAK data received from my supervisor and further restricted it to violent crimes, coordinates, and time of the crime. Moreover, I facilitated the analysis to include temporal factors of the violent crime distribution in Oslo. To make the data time-dependent (Hardyns and Rummens, 2018), the dates of the reported crimes were categorised into 52 weeks in each year from January 2016 to December 2020 to measure the crime historical and seasonal trends in violent crime patterns. There were no missing values in the time variable, therefore, no exclusion of missing observations was necessary. Furthermore, grid cells that had no registered crimes at any point throughout the entire period was excluded from the analysis to reduce noise and the imbalance in the data resulting from a large number of empty grid cells. Such exclusion is further justified by the unlikely occurrence of crime in such areas in the future, including water areas, forests, and other locations with limited human activity.

Data integration

Data integration is an important step in the work of crime prediction (Nguyen et al., 2017). To be able to perform the random forest analysis of violent crimes in Oslo, I have merged the STRASAK, OSM and MET data into a new dataset, based on their location and time stamp.

Feature engineering

The process of crafting, selecting, and scaling features in the dataset can be considered feature engineering. This step is often applied when uncovering and explaining the predictor response relationship in the data. By transforming the raw data into features, they can be applied in the machine learning model to unlock predictors essential to the predictive information related to the outcome (Kuhn and Johnson, 2019). In this step, I created features with weekly crime data and spatiotemporal time lags. More specifically, the violent criminal events were aggregated into a temporal series of crime events on a weekly trend for each grid and were then further decomposed into autoregressive lags that were used as features in the random forest analyses. When using fixed time intervals and spatial units, it is important to account for temporary hotspots and violent crimes that occur across the boundaries of these fixed units (Gorr and Lee, 2015). Therefore, adjacent cells were created to account for the spatial and temporal autocorrelations and reduce a possible biased assessment of the model (Meyer et al., 2018 in Lovelace, Nowosad and Muenchow, 2019). Moreover, Waldo Tobler's (1970 in Lovelace et al., 2019: 259) first law of geography: *"Everything is related to everything else, but near things are more related than distant things",* highlights the importance of considering the spatiotemporal dependencies, friction of distance or the effect of proximity, when analysing the basis of spatial patterns and relationships. Following Tobler's law of geography, spatial prediction maps with adjacent cells can be used as a central tool to test for the independence of spatial coordinates. Similarly, these adjacent cells can be utilised to track and identify the changing trends of violent crime patterns over successive time periods (Xia et al., 2021).

On that note, I chose to include a weekly time analysis in my data because, as suggested in the literature review, crime opportunities are not uniformly distributed in space, and it can be important for detecting the spatial change in the registered crimes (Brantingham and Brantingham, 1993a; Newton and Felson, 2015; Ratcliffe, 2006; Xia et al., 2021). Similarly, adding temporal time lag features can help the model detect the relationship between time periods and the spatial dependencies on neighbouring cells (Xia et al., 2021). If spatio-temporal patterns are present, it means that a crime impacts the risk for a future crime in nearby places and that this risk is changing over time. Using a weekly crime analysis along with crime data can, therefore, increase the likelihood of identifying violent crime patterns in high-crime areas and uncover how violent crimes may be spatially constrained by nodes or along pathways leading to nodes (Kounadi et al., 2020). On the other hand, the feature engineering process may be time-consuming and requires domain knowledge when dealing with large spatiotemporal datasets. For this reason, some previous studies lack transparent reporting on feature engineering procedures (Kounadi et al., 2020). Consequently, it can be challenging to reproduce the proposed methodology when the procedure of assigning features is insufficiently reported (Kounadi et al., 2020). For reproducibility and credibility, this thesis has sufficiently documented the unit of analysis and sample size.

Random sampling

To handle imbalanced classification issues, there are two common schemes for random sampling of the data: over-sampling, and under-sampling. Over-sampling involves randomly duplicating observations from the minority class and under-sampling randomly removes observations from the majority class (Drummond and Holte, 2003). By under-sampling the data, I could balance the classes and generate a transformed version of the data, which enabled the machine learning model to remove any bias towards the majority class. Moreover, Drummond and Holte (2003) found in their research that over-sampling the data could lead to overfitting, thus, making this technique ineffective compared to under-sampling. The importance of avoiding overfitting or underfitting the data will be further discussed in the subsequent section on machine learning. Under-sampling can contribute to a reasonable baseline for algorithmic comparison. Additionally, Lin et al. (2018) found that the data would not outweigh the crimes recorded when removing grid cells with no recorded crimes to prevent non-occurring crime categories. Based on Drummond and Holte's (2003) and Lin et al.'s (2018) argument, a high ratio of cells with no registered crimes was eliminated from the data, and the borders of the map were limited by cutting the adjacent nature area "Marka". Removing Marka also reduced the possibility of indirectly identifying people that live in very low-populated areas, which is important out of privacy considerations. On that note, although under-sampling appears to be the preferred strategy for resampling the data, there is still a chance of losing essential information when reducing the dimensionality. While reducing the dimensionality by excluding Marka may carry the risk of losing essential information, it is highly unlikely since Marka predominantly consists of natural terrain (see Figure 1).

Using machine learning to predict violent crime

Machine learning, at the core of data science and AI, is one of today's fastest-expanding technical fields and lies at the intersection of statistics and computer science (Jordan and Mitchell, 2015). By enabling algorithms to detect patterns within a range of data types, including but not limited to numerical data, text and images, machine learning serves as a powerful tool that can be used to process information within the obtainable data. Algorithms, in this thesis, understood as sequences of instructions carried out to transform and predict inputs given certain outputs (Alpaydin, 2014; Jung et al., 1993), are used in machine learning in various ways to address how to build a model that automatically improves through experience. Consequently, machine learning consists of two key components: an algorithm to model relationships between dependent and independent variables and a learning process that aims to select the most accurate match for the independent variable (Jung et al., 1993). Therefore, creating a model that will improve automatically through experience allows researchers to develop new theories and learning algorithms by implementing data-intensive machine learning methods (Jordan and Mitchell, 2015). Furthermore, classical machine learning can be split into three categories; Unsupervised learning, which has no specific output defined, where the goal is to detect a pattern based on the observed input variables; Reinforcement learning, which involves maximising rewards from interacting with the environment where the model relies on its own experience to learn how to generate the correct action; Supervised machine learning which involves training a model where the output required is identified even though the specific relationship in the data is unknown (Jung et al., 1993; Qiang and Zhongli, 2011).

To predict the locations of violent crimes in Oslo, supervised machine learning algorithms were utilised to predict new or unseen patterns in the data. By implementing a supervised learning method, the study aims to contribute to understanding crime patterns in Oslo and provide insightful knowledge for better crime prevention strategies. Moreover, it is necessary to differentiate between classification and regression models to better understand the different ways of employing unique machine learning techniques. Classification, in machine learning, classifies the data into, for example, 0 or 1 (Alpaydin, 2014). This algorithm distributes the data into classes and is a common supervised machine learning method (Saeed, Sarim, Usmani et al., 2015). On the other hand, a regression model can predict continuous variables and measure the relationship between the feature and outcome variables (Alpaydin, 2014). The most significant difference between these techniques is that classification predicts discrete variables, while regression is used on continuous data. Because the target variable at hand is discrete and not continuous, this thesis relies upon data classification or pattern recognition instead of regression methods. Since classification has been shown to effectively predict potential risks in the criminal justice system related to individuals posing a higher threat to society upon release or used on broader criminal justice decisions (Berk and Bleich, 2013; Oh et al., 2021), it is reasonable to consider classification as a potentially effective technique for predicting the spatial and temporal location of violent crimes. Therefore, I employed a supervised machine learning algorithm to establish a conceptual model for analysing and predicting the shifting trends in violent crime patterns across different spatial and temporal dimensions by building upon the pattern recognition capabilities inherent in classification.

Finally, when working with complex statistical models and analyses, it is essential to consider the potential contamination of the data through a phenomenon known as the *bias-variance trade-off,* which includes *underfitting* or *overfitting* of the model at hand (Alpaydin, 2014; James et al., 2013). The concept of a bias-variance trade-off suggests that there should be an optimal balance between model simplicity and complexity to produce generalisable results (James et al., 2013). One solution can be splitting the data into training and test sets to eliminate bias in a model's learning process and protect it from statistical interference. Eliminating bias helps increase the model's performance and make the results more generalisable for future data analysis. An underfit model has high bias and low variance, and the model's poor performance might stem from a lack of capacity to capture the underlying patterns in the data. Conversely, an overfit model has high variance and low bias. An excessive variance in a model may lead to capturing random fluctuations or noise in the data by mistaking the noise for a pattern (James et al., 2013). Therefore, to reduce overfitting in my model, I performed feature selection after splitting the data into a training and test set, which involved identifying and eliminating variables that could have introduced noise or irrelevant information. Moreover, it is possible to achieve a trade-off concerning the delicate balance between bias and variance by splitting the data into training and test sets so that it will not fail when predicting new data (James et al., 2013; Kuhn and Johnson, 2019). On the other hand, Breiman (2001) claims that random forest models are not subject to overfitting and that the accuracy depends on the strength of each tree classifier. Nevertheless, it is still essential to be aware of the possibility of a bias-variance trade-off (Wheeler and Steenbeek, 2021).

Splitting the data into train and test sets

Separating the dataset into a training set and a test set is a common, and necessary, practice to avoid contamination by overfitting the data (Berk and Bleich, 2013; Kuhn and Johnson, 2019). Therefore, I split the dataset into 70 per cent training data to train or teach the model how to make predictions based on unseen data and to estimate the model's performance (James et al., 2013). The remaining 30 per cent of the dataset was used as a test set to evaluate the trained model's ability to generalise and make predictions on new, or unseen data, for future analyses of violent crime patterns (Kuhn and Johnson, 2019).

Feature selection

Arguably, reducing dimensionality is an essential step in the pre-processing stage (Alpaydin, 2014), and can help simplify the data by removing unimportant or redundant features (Babakura et al., 2014; Vieira, Kaymak and Sousa, 2010). Here, feature selection is used to identify and re-represent predictors in the predictive modelling framework as far as possible without compromising the model's predictive performance (Kuhn and Johnson, 2019). Explicitly, the *wrapper method* for feature selection was applied to select the best set of predictors in the training data (Vieira et al., 2010). The wrapper method is a process of repeatedly trying different subsets of predictors and checking their performance to help guide the selection and evaluation of the following subset (Kuhn and Johnson, 2019). More specifically, I used backward feature selection, or recursive feature elimination (RFE), which involved selecting all predictors and removing the least necessary predictor, one by one until, a smaller set of predictors was left. This feature selection technique is performed before the random forest analysis to maximise the accuracy and generalisability of the model.

Moreover, the RFE technique was applied to rebuild the computed importance score for each selected feature. It utilised a *tuning parameter* to subset the size, enhancing the performance criteria for selecting predictors based on the importance rankings. Therefore, the RFE method can be classified as a *greedy approach* due to its optimal feature selection technique: choosing the path that seems best at the time to achieve the best results without considering how these results could impact future paths (Kuhn and Johnson, 2019). On the other hand, Kuhn and Johnson (2019) contend that there may be better fits than this approach if significant interactions between predictors are not considered. To mitigate this problem, I ran the RFE multiple times. I averaged the importance of each variable using cross-validation in Caret, a package in R, before selecting the most essential variables for the random forest model. Similarly, by selecting the most significant features, thereby eliminating the remaining features that are not equally important, the machine learning model could be simplified by reducing the dimensionality of the data, or its complexity, leading to an increased model performance by removing noise in the data. This feature selection process allowed the RFE model to identify the most critical predictors used to determine the model's accuracy. As a result, I could manage high-dimensional data while simultaneously extracting essential characteristics by reducing its dimensionality.

Random forest

Random forest is a powerful learning algorithm that uses a combination of predictors shaped by multiple decision trees where each tree's structure is dependent on the values of a randomly selected vector (Breiman, 2001). Random forest models can be used for regression or classification, including crime prediction, and quantifying the importance of urban indicators (Alves et al., 2018; Berk, 2010). Consequently, with an ensemble of smaller models, the random forest has a remarkable forecasting accuracy and performance in modelling non-linear relationships (Alves et al., 2018; Berk and Bleich, 2013). Additionally, the random forest will still perform well even though irrelevant features are included in the data, making this learning-based algorithm suitable for predicting violent crimes (Hapfelmeier and Ulm, 2013).

In statistical terms, the random forest algorithm classifies data by randomly selecting predictors and subsamples to construct decision trees. The random forest then combines the decision trees to generate a consensus prediction (Oh et al., 2021), creating an ensemble model constructed by considering a random subset of predictors at each split (Zhang et al., 2020). This intentional randomisation process helps to decorrelate the trees, leading to a decrease in the variance and an increase in the reliability of the model (James et al., 2013). While this improvement happens at the expense of the interpretation (James et al., 2013), Oh, et al. (2021) contend that it can enable the random forest algorithm to outperform other statistical models.

To generate the set of random samples used in the random forest model, *bootstrap aggregation,* or *bagging*, is applied to increase the flexibility of the model while reducing the variance in the random forest model and is frequently used in the context of decision trees (James et al., 2013). Bagging is applied to ensure that the random forest classification does not overfit when a large number of trees are grown and is essential for optimising the classification objectives of the random forest model (Berk, 2010; Suthaharan, 2015; Zhang et al., 2020). During the training phase of the model, the random forest model employs the bootstrapping technique by generating a number of random sub-samples from the original dataset with replacements. By allowing observations of the original dataset to be repeated in several sub-samples, the bootstrapping process introduces variability and diversity into the training data. Whereas bagging is applied during the testing phase of the algorithm and works by averaging all of the predictions from the different sub-samples created using the bootstrapping technique to obtain the final classification (Suthaharan,2016). Subsequently, for each node, the split attribute set is selected randomly from the K best splits through a *random split selection* (Breiman, 2001; Zhang et al., 2020). Then, the new training set is generated by randomising the outputs in the original training set. As a result, bagging can test the algorithm by evaluating the performance of the classifiers.

Ethical considerations

In this thesis, the aim was to map the place of a registered violent offence in Oslo from 2016 to 2020. Although this thesis did not research individuals or crimes on a personal level, due to the significant risk to the data subjects' freedoms and rights, precautions were taken before the commencement of any analytical procedures to secure the anonymity and confidentiality of any data related to this project. This data has been granted a privacy impact assessment (DPIA) since the original data contains privacy information regarding registered offences and addresses. The dataset, as a part of police reporting routines, was restricted to a subset of the STRASAK data by my supervisor to guarantee that this project would not contain any sensitive information irrelevant to this research.

This research study was approved by the Norwegian Agency for Shared Services in Education and Research (SIKT, previously NSD) and the National Police Directorate (POD) through my supervisor's project "Mapping and forecasting crime trends in smaller cities – relevance for Norwegian Research and Policing" (SIKT ref. nr. 130356)[11]. Therefore, my supervisor was responsible for the overall processing of any data connected to this project. The Norwegian

[11] Approval was received for retrieving and handling data gathered from the police crime registers STRASAK and PAL for PO. This approval includes the possibility to share subsets of this data with master students at the University of Oslo and receive automatic approval for their projects. Upon consulting with SIKT, it was concluded that no additional approval was necessary for this thesis application.

Police University College (NPUC) and the Faculty of Law at the University of Oslo (UiO) had a joint institutional responsibility.

To further ensure complete anonymity and confidentiality, physical access to the data was required through services for sensitive data (TSD). TSD functioned as a remote desktop delivered by the University of Oslo which complied with the Norwegian law for information safety and ensured secure data handling according to the General Data Protection Law (GDPR). Henceforth, TSD allowed all statistical analyses to be conducted in this secure environment. Consequently, the crime data was anonymised through spatial aggregation and the data handling and exportation was approved for publication by my supervisor in accordance with the University of Oslo's existing sensitive data legislation (Haygen and Skilbrei, 2021; UiO, n.d.). For example, the choice to employ grid cells of 100x100m and more were deliberately made to avoid distributing confidential information that could challenge the attainment of anonymity and identification of any actors involved at the crime scenes. Additionally, the research was conducted following the guidelines for Research ethics by the Norwegian national research ethics committees (NESH, 2019) and the Research ethic guide at the Norwegian Police University College (Bjørgo and Myhrer, 2015).

The researcher's ethical responsibility and integrity

For the duration of this research, I was responsible for following ethical principles and upholding an honest approach towards reporting results from the analyses presented in this thesis. To assure transparency and that the results presented in this paper are reliable and valid, the data has been presented accurately with a reproducible code[12] to secure any validity to the project and its findings. While this study may function as an initiative for new policies and can contribute to new findings in the criminological field of environmental crime, the outcome and result of this study were interpreted objectively and realistically.

[12] If it is deemed necessary to verify the validity of this project, the reader may contact the author for further information and clarification. The author's details can be found by contacting the Faculty of Law at the University of Oslo.

Results

The following section provides a comprehensive overview of the results and findings obtained through statistical data analysis and information about violent crimes in Oslo. This section presents the random forest analysis results and investigates how various environmental factors can influence these violent crimes. Additionally, some descriptive statistics and maps are included to visualise the frequency and spatial distribution of violent crimes in Oslo from 2016 to 2020.

Descriptive analysis

Frequency of reported violent crimes

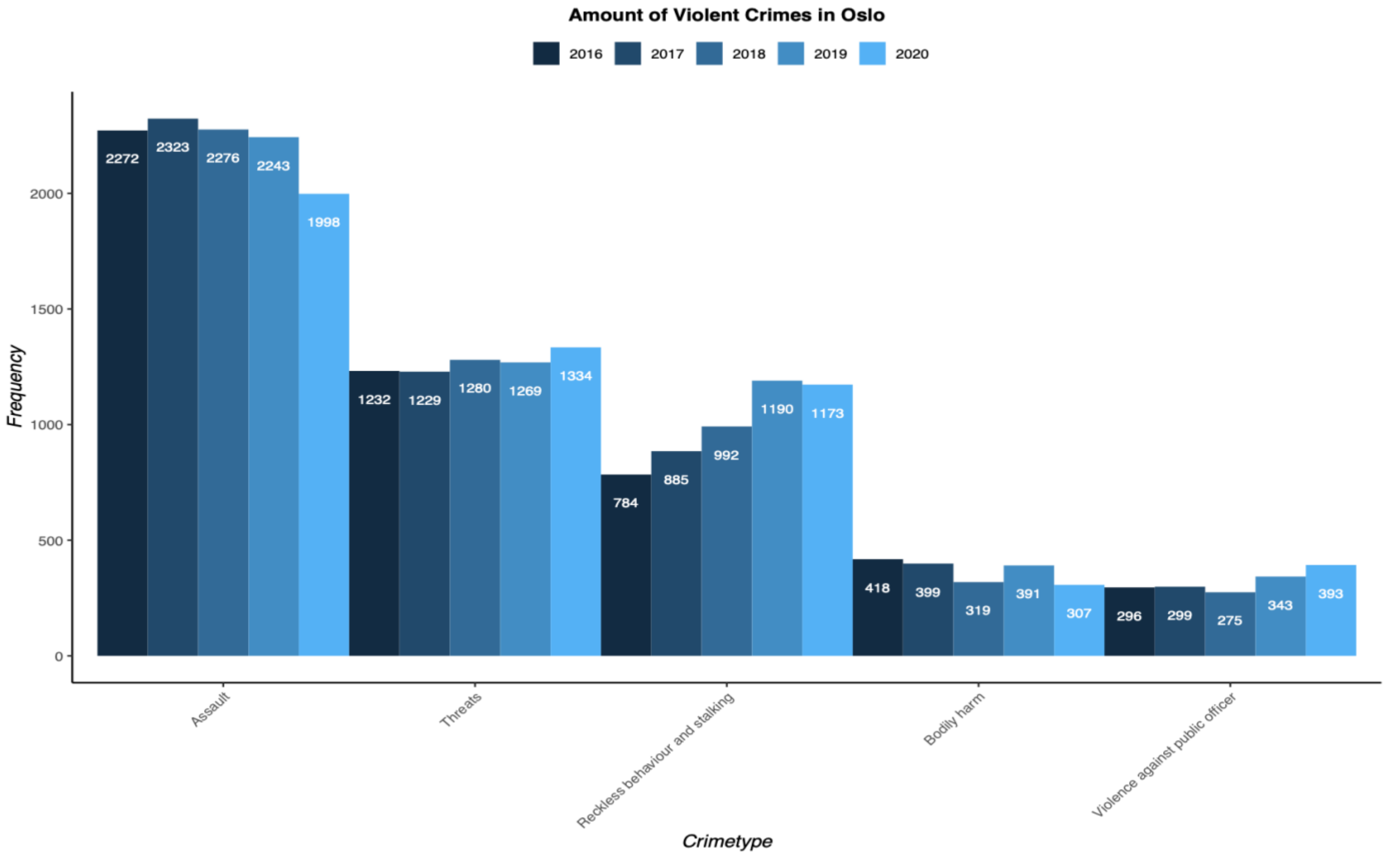

Figure 2: Frequencies of violent crimes in Oslo

Frequency of Reported Violent Crimes based on Time of Day

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
00-04	1908	1865	1845	1851	2232	2646	3111	**15458**
05-09	304	316	313	354	345	320	389	**2341**
10-14	747	806	796	722	787	593	506	**4957**
15-19	899	936	951	883	989	901	722	**6281**
20-23	649	698	702	747	962	999	614	**5371**
Total	**4507**	**4621**	**4607**	**4557**	**5315**	**5459**	**5342**	**34408**

Table 1: Frequency of reported violent crimes

Figure 2 demonstrates the frequencies of the city's five most commonly reported violent crime categories. Among these crimes, assault is the most frequently reported, accounting for 32 per cent of all violent crimes in total. Assault peaked at 2323 crimes in 2017 and decreased to 1998 reported crimes in 2020. In total, there were registered 11 112 assaults from 2016 to 2020. The second most frequently reported violent crime is threats, accounting for almost one in five crimes with a total of 6644 registered crimes. More interestingly, reckless behaviour and stalking increased with approximately 50 per cent from 2016 to 2020, with a total of 5024 registered crimes. Furthermore, bodily harm accounts for 1834 of the violent crimes registered in the period, while violence against public officer accounts for 1606 of the registered crimes. This leaves 8188 violent crimes in other categories making up 23 per cent of all violent crimes[13]. Overall, 2019 is the year with the highest number of reported crimes, totalling 7126 crimes. Conversely, 2016 has the lowest number of reported crimes in the period, with 6652. Furthermore, Table 1 exhibits the hourly and daily distribution of violent crime patterns in Oslo from 2016 to 2020. The data suggest that incidents of violent crimes reach their maximum between the hours of 00:00 to 04:00 on weekends and, conversely, reach their lowest point during the period of 05:00 to 09:00 from Monday to Thursday. Specifically, there were 15,458 reported instances of violent crimes in Oslo from midnight to 4 am and constituting 45 per cent of all registered crimes with 21 per cent overall increase in violent criminal incidents from Mondays to Saturdays.

[13] The remaining violent crime categories include robbery, extortion, coercion, deprivation of liberty, human trafficking, terror-related offences, and miscellaneous types of violence or maltreatment.

Time series analysis of reported violent crimes

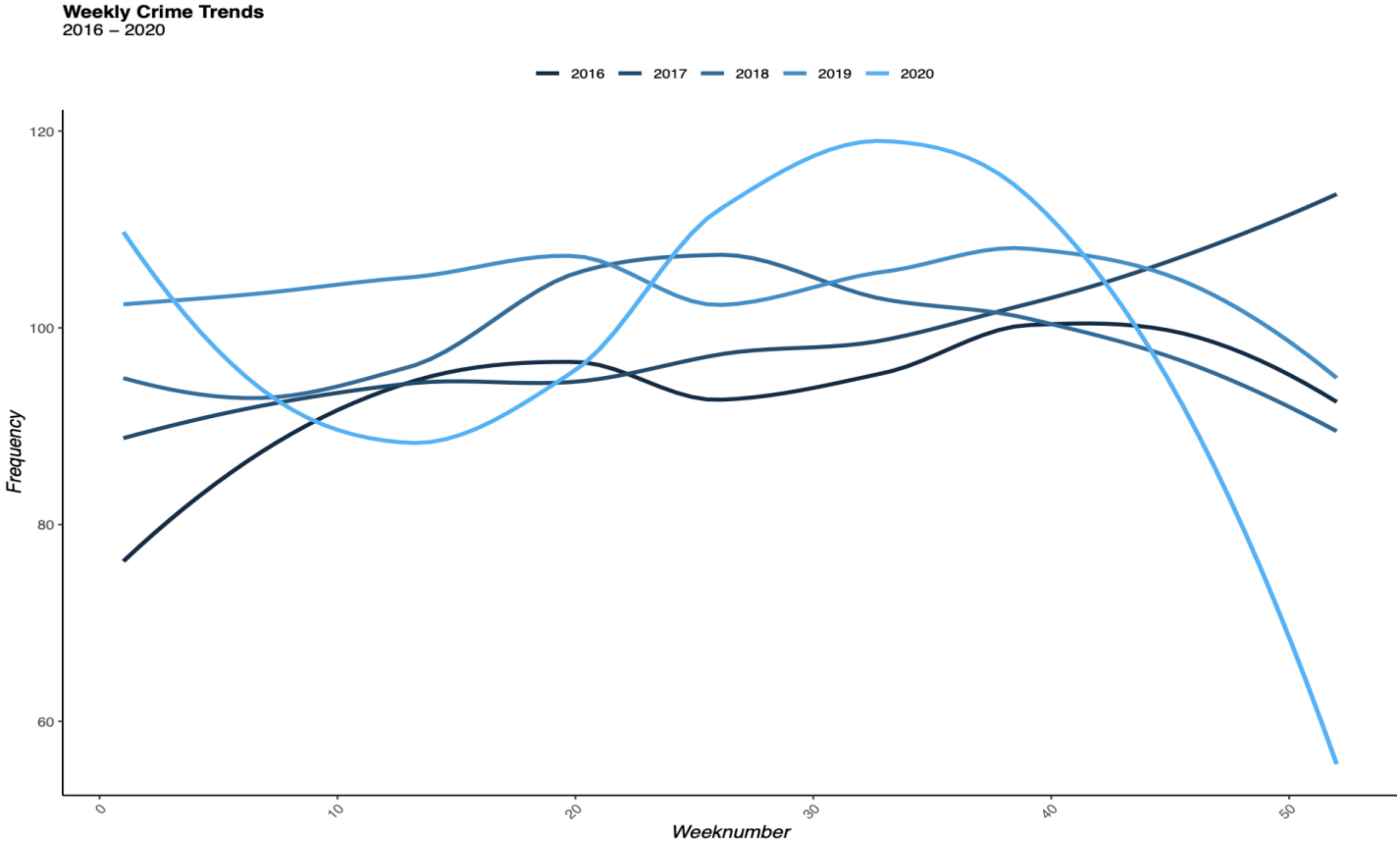

Figure 3: Distribution of violent crimes in Oslo across time

Furthermore, the time series analysis in Figure 3 examines the distribution of reported violent crimes each week in Oslo over time. The results indicate that the frequency of violent crimes in Oslo peaks in 2020 between weeks 30 and 40, followed by a significant decrease towards the end of the year. According to the report, there were around 120 crimes reported during the summer to the autumn period of 2020, while the number of reported crimes decreased to less than 60 during the winter. In 2017, the number of reported violent crimes started at approximately 90 and increased to over 100 towards the end of the year. Conversely, in 2016, 2018, and 2019, the frequency of violent crimes remained relatively stable throughout the year, with a slight increase during the summer months and a decrease in the winter.

Pearson's correlation analysis

	Row Names	Violent Crime
100x100m	Footway	0.336
	Time lag	0.223
	Place of crime	- 0.016
	Forest	-0.283
250x250m	Bicycle parking	0.347
	Time lag	0.289
	Place of crime	0.007
	Forest	-0.281
500x500m	Pedestrian	0.361
	Time lag	0.334
	Place of crime	0.025
	Forest	-0.237

Table 2: Pearson's correlation

Being cognisant that correlation does not imply causation is fundamental to reducing the risk of drawing incorrect conclusions. The present study implements Pearson's correlation as a statistical method to measure the correlation between the predictors and violent crimes. The correlation analysis is performed for each grid cell size on the map, and no predictors display a correlation greater than 0.361 or less than -0.283. For the 100x100m map, footway exhibits a positive correlation of 0.336 with violent crimes, whereas forest displays a negative correlation of -0.283. In the 250x250m map, Bicycle parking shows a positive correlation of 0.347 with violent crimes, and forest reveals a negative correlation of -0.281. Finally, in the 500x500m map, pedestrians exhibit a positive correlation of 0.361, while forests show a negative correlation of -0.237. Additionally, the correlation between the time lag and place of crime is reported in Table 2 for clarity.

Geospatial patterns of violent crime incidents in Oslo

Three distinct maps were created to visualise the predicted violent crime patterns in Oslo, varying in size with dimensions of 100x100m, 250x250m, and 500x500m grid cells. These maps were created to visually represent the forecasted crime patterns in different levels of detail. The grid cells in the map were assigned colour codes based on the predicted level of violent crimes within each cell.

Equation 1 - Normalisation

$$X = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The values are normalised on a 0 to 1 scale using Equation 1. Grids with the 25 per cent highest number of crimes are defined by red grid cells, while blue grid cells represent the remaining predicted crimes, becoming darker with increasing crime levels. Moreover, white grid cells indicate areas with zero predicted crimes. In contrast, grey cells are not included in the predictions because they were not selected in the model after the random undersampling of the data. Additionally, the grey grid cells include cells with a consistent lack of recorded violent crimes and are, therefore, not considered in the final analysis. For all maps, the highest density of crimes is located within the inner city and spreads towards the eastern part of Oslo. Conversely, there is a notable scarcity of predicted violent crimes in the western part of the city.

*Map with 100x100*m *grid cells and predictions*

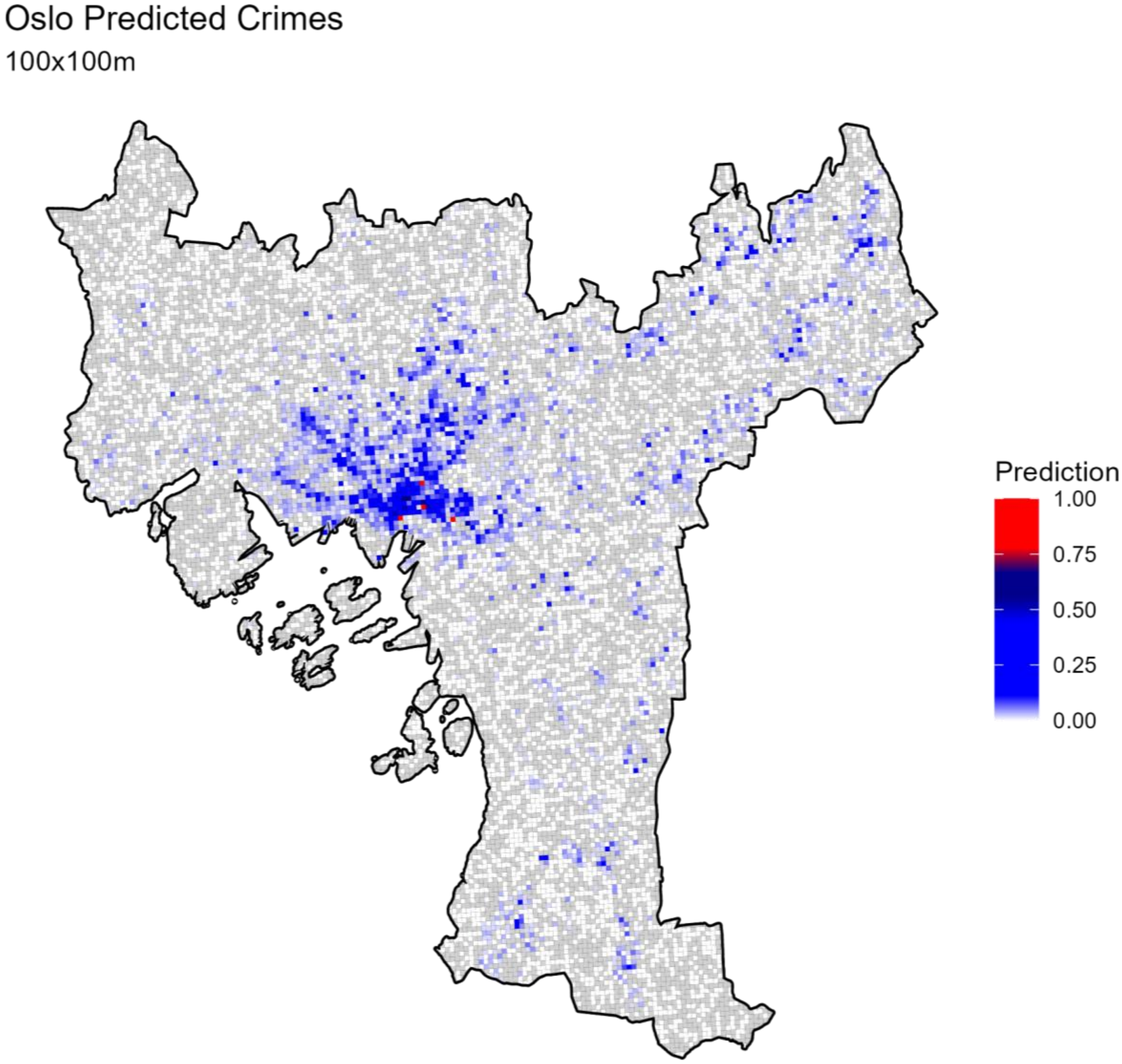

Figure 4: Distribution of predicted violent crimes in Oslo 100x100m

Figure 4 shows that most predicted crimes are concentrated in the central business district and the inner city. While the west and east areas have fewer predicted crimes, there are more crimes predicted in the eastern part of Oslo compared to the western part. Near the central station in the central business district, there is an unoccupied grid cell adjacent to a high-crime grid cell. This indicates that a building spans across multiple grid cells, but its address is registered to only one of them. Moreover, the substantial presence of grey areas suggests that the analysis did not include a significant number of grid cells. This could be attributed to the small size of the cells and the overall low occurrence of crimes within each individual cell.

*Map with 250x250*m *grid cells and predictions*

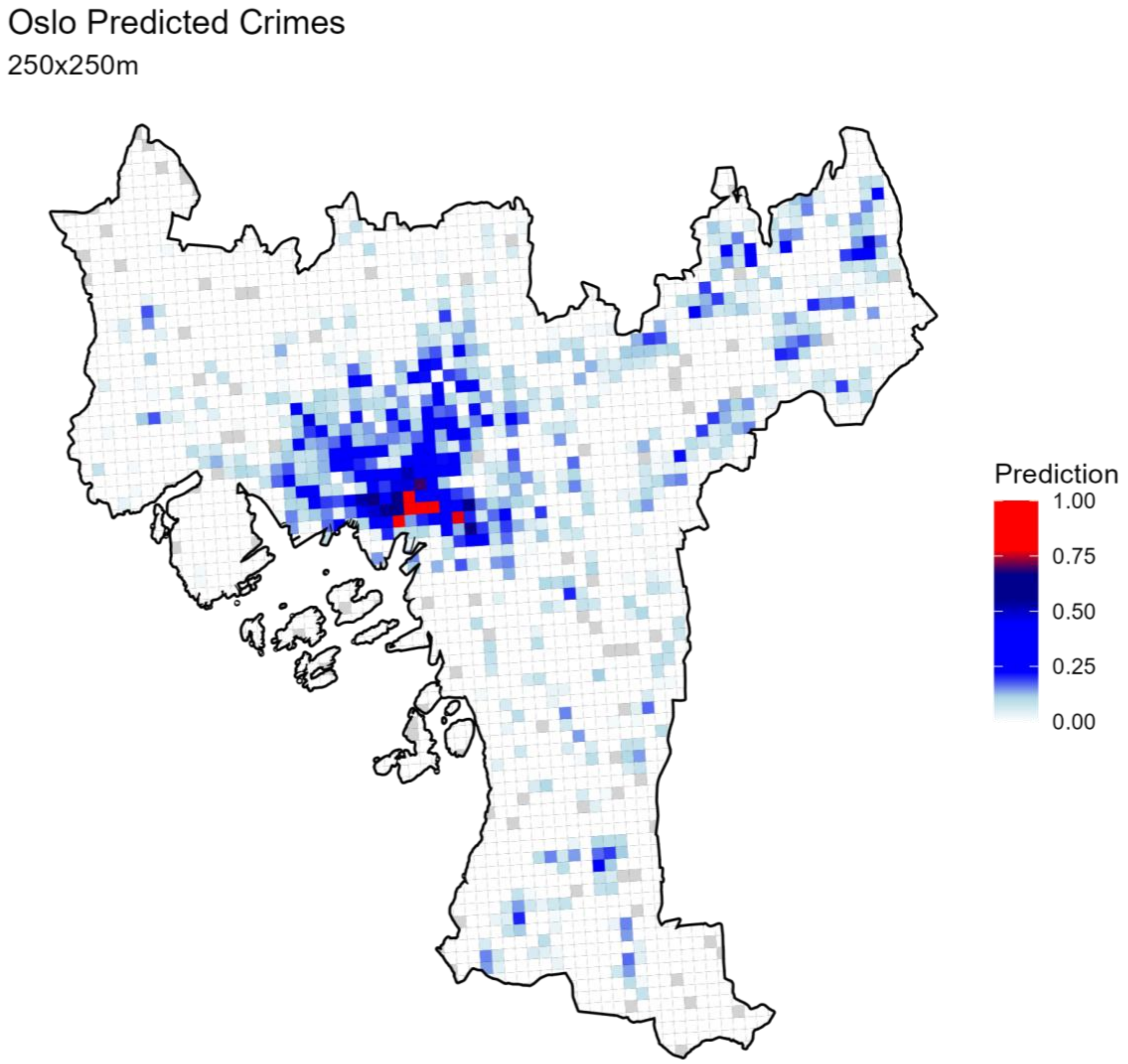

Figure 5: Distribution of predicted violent crimes in Oslo 250x250m

In Figure 5, the density of predicted crimes remains high in the central business district and the eastern part of Oslo, indicating that most crimes are likely to occur within Oslo's inner city limits. Still, there are more reported crimes in the east than in the west part of Oslo when the map is set to 250x250m grid cells. There are still grey areas that were not included in the model, but remarkably fewer than in the 100x100m grid cell map in Figure 4.

*Map with 500x500*m *grid cells and predictions*

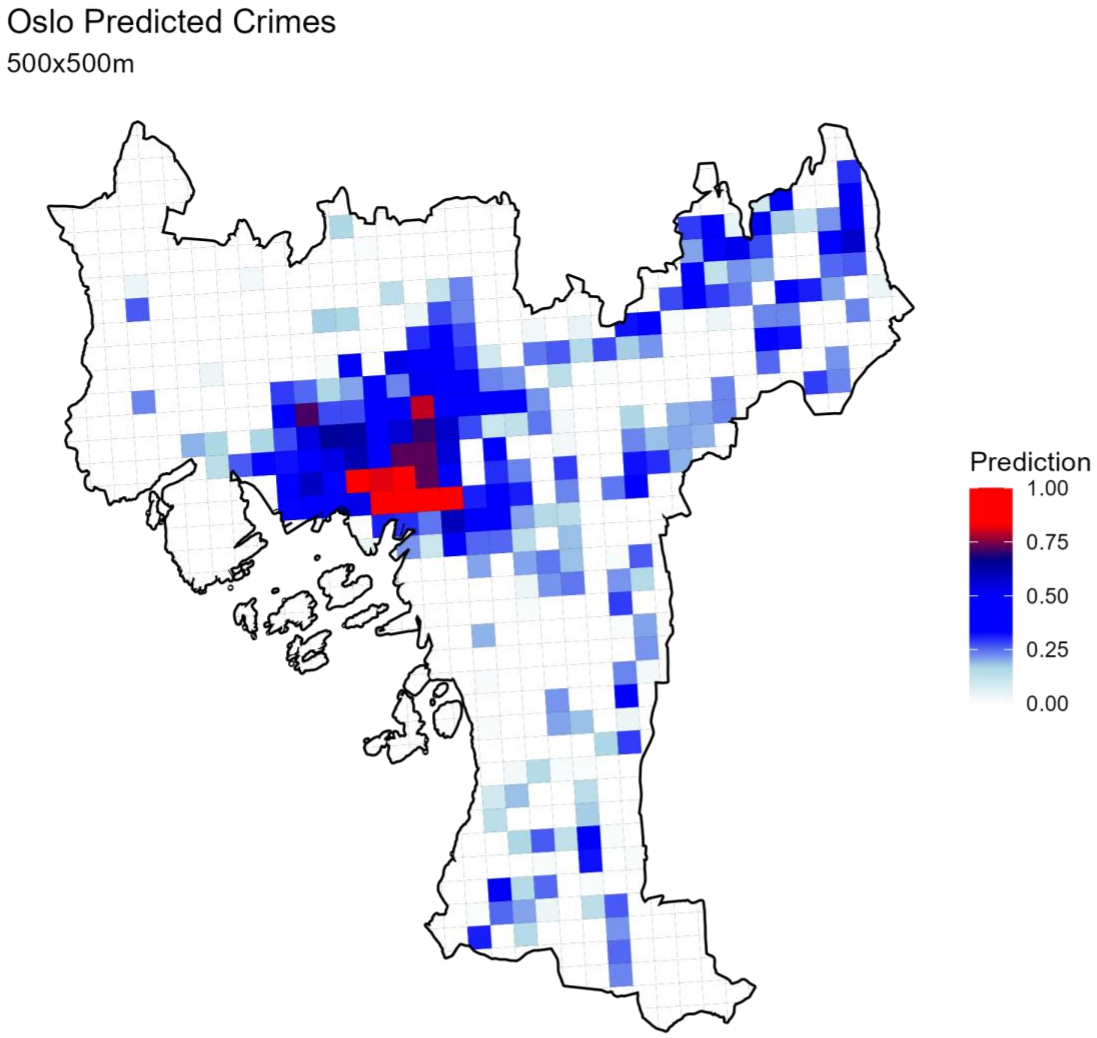

Figure 6: Distribution of predicted violent crimes in Oslo 500x500m

Figure 6 provides a clearer visualisation of the areas with high and low predicted crime rates, with the grid cell size increased to 500x500m. Again, the majority of predicted crimes are concentrated in the central business district and the eastern part of Oslo. While there are predicted crimes in the western region, they are infrequent, as indicated by the few grid cells displaying a blue colour. From these three figures (Figures 4, 5 and 6), the results suggest that the use of random forest analysis can help predict crime patterns in urban areas, especially in densely populated areas such as in the inner city of Oslo. In this model, there were no grey areas included, meaning some values fell into each grid cell, and all grid cells were measured in the random forest analysis.

Random forest analyses

A random forest analysis enables the prediction of violent crime patterns and estimates how much the various environmental features may influence these crimes. All random forest models were run with 500 trees and data from STRASAK, MET and OSM. The following section elaborates on the results and presents the outcomes of each random forest prediction analysis.

The first random forest Model 1 is performed with grid cells of 100x100 meters on the Oslo map. Here, Model 1 predicts that footway[14] and forest[15] are among the traits that influences violent crimes on a geographical level. The second random forest Model 2 is performed with grid cells of 250x250 meters. This model predicts that residential areas and living streets[16] are among the traits that can influence violent crimes in Oslo. Moreover, Model 3, performed with grid cells of 500x500 meters, predicts that living streets and smaller local roads are significant for predicting crimes. All models agreed that place of crime is the most essential variable for predicting violent crime in Oslo. Similarly, Model 1 and Model 2 agrees that time lags are significant for predicting crime. The findings will now be discussed further in detail.

Recursive Feature Elimination (RFE)

The RFE technique is applied to identify the most essential features with the greatest impact on the model's predictive performance. In this study, the feature selection process is based on cross-validation with 5-folds which means the model iteratively removes the least significant predictors as determined by the cross-validation performance. The feature selection allows the model to identify the optimal number of predictors that will balance the model's performance and complexity. Furthermore, the accuracy measure derived from the RFE indicates the RFE model's overall performance in accurately classifying instances. In this analysis, all results of the RFE are in descending order based on their predictive power in identifying violent crimes in Oslo.

Notably, the RFE analyses reveals that place of crime is consistently identified as the most crucial feature in all models. This finding underlines the significance of hotspots and crime clusters for predicting violent crimes in Oslo. Nevertheless, it is critical to emphasise that the

[14] Footpaths.

[15] A forest or woodland.

[16] Streets where pedestrians have priority over cars.

results of the RFE process should not be taken as absolute but as one solution among many. The RFE results are used to refine the random forest model by selecting the most significant features. Then, when the random forest model was built, only the predictors that demonstrate superior performance in cross-validation were included based on their accuracy, and Kappa measures from the RFE model. The inclusion of Kappa is particularly valuable, as it provides a normalised classification accuracy at the baseline of random chance in the dataset and a more comprehensive evaluation of the model's performance beyond the accuracy alone (Vieira et al., 2010). The Kappa measures the agreement between the predicted and actual values, where a higher value indicates a better agreement.

Recursive feature elimination 100x100m *5-fold Cross-Validation*

	Variables	Accuracy	Kappa	AccuracySD	KappaSD	Selected
*	70	0.7838	0.5675	0.003539	0.007083	*
	50	0.7829	0.5658	0.004615	0.009233	
	60	0.7822	0.5644	0.003675	0.00735	
	80	0.7821	0.5641	0.004941	0.00989	
	100	0.7818	0.5637	0.004146	0.008295	
	40	0.7803	0.5605	0.004247	0.008496	
	120	0.7763	0.5525	0.004363	0.008727	
	30	0.7744	0.5487	0.005503	0.011003	
	151	0.7743	0.5485	0.003267	0.006538	
	20	0.7599	0.5197	0.003699	0.007399	
	15	0.7447	0.4894	0.004166	0.008335	
	10	0.7332	0.4663	0.006818	0.013623	
	5	0.7055	0.411	0.004882	0.009765	

* The top 5 variables (out of 70): Place of crime, footway, residential, scrub, forest

Table 3: Recursive feature elimination Model 1

The RFE for Model 1 found that 70 specific factors are important for predicting violent crimes in Oslo and could correctly classify 78.38 per cent of the cases in the data used to fit the model. Though looking at the accuracy for all predictors in Model 1, it is evident that every set of predictors could correctly classify at least 70.55 per cent of where the violent crimes in Oslo will happen. To measure the accuracy for classification in Model 1, the kappa is 0.5675, indicating a moderate level of agreement beyond what would be expected by chance alone. This agreement suggests that the model is performing better than random guessing, but there is still room for improvement in the level of agreement between predicted and actual labels. Moreover, Model 1 demonstrates that the place of crime, footway, residential, scrub and forest are among the top 5 features out of 70.

Recursive feature elimination 250x250m *5-fold Cross-Validation*

	Variables	Accuracy	Kappa	AccuracySD	KappaSD	Selected
*	120	0.7730	0.5460	0.0081	0.0162	*
	100	0.7726	0.5451	0.0083	0.0165	
	40	0.7725	0.5451	0.0092	0.0184	
	50	0.7725	0.5450	0.0101	0.0202	
	80	0.7722	0.5444	0.0093	0.0186	
	30	0.7719	0.5439	0.0094	0.0187	
	60	0.7716	0.5433	0.0089	0.0178	
	70	0.7716	0.5433	0.0091	0.0182	
	151	0.7714	0.5428	0.0080	0.0159	
	20	0.7686	0.5372	0.0091	0.0181	
	15	0.7499	0.4998	0.0068	0.0136	
	10	0.7347	0.4695	0.0082	0.0164	
	5	0.6924	0.3848	0.0121	0.0243	

* The top 5 variables (out of 120): Place of crime, residential, pedestrian, steps, Bicycle parking

Table 4: Recursive feature elimination Model 2

In Model 2, the set of 120 predictors have a 77.30 per cent accuracy in classifying all instances of violent crimes in Oslo when the grid cells are 250x250m. The Kappa value is 0.5460, suggesting Model 2 performs better than randomly guessing the predicted value, while this model has room for improvement. For Model 2, the place of crime, residential, pedestrian, steps and bicycle parking are among the top 5 predictors of violent crimes out of 120.

Recursive feature elimination 500x500m					*5-fold Cross-Validation*
Variables	**Accuracy**	**Kappa**	**AccuracySD**	**KappaSD**	**Selected**
* 20	0.761	0.5219	0.004653	0.009304	*
30	0.7605	0.521	0.00369	0.00738	
120	0.7595	0.519	0.003025	0.00605	
151	0.759	0.518	0.004015	0.00803	
80	0.7587	0.5174	0.005463	0.010925	
100	0.7586	0.5171	0.004064	0.008129	
70	0.7583	0.5167	0.004404	0.008808	
40	0.7579	0.5157	0.004595	0.009191	
60	0.7579	0.5157	0.004067	0.008134	
50	0.7569	0.5138	0.003687	0.007375	
15	0.755	0.5101	0.002779	0.005559	
10	0.7423	0.4845	0.004623	0.009243	
5	0.7164	0.4329	0.003292	0.006583	

* The top 5 variables (out of 20): Pedestrian, place of crime, steps, bicycle parking, playground

Table 5: Recursive feature elimination Model 3

Furthermore, Model 3 favours a set of 20 predictors to correctly classify 76.10 per cent of the violent crimes in Oslo. Here, the Kappa value decrease to 0.5219, which means there is still a moderate agreement between the actual and predicted values. Out of the 20 predictors in Model 3, pedestrians, places of crime, steps, bicycle parking, and playground are among the top 5 predictors of violent crimes.

In summary, the 100x100m grid map appear more favourable than 250x250m and 500x500m grid map in terms of prediction accuracy when predicting violent crimes in Oslo. Additionally, the higher Kappa value further supports Model 1 as performing moderately better than random chance.

Confusion matrix

Operating uniformly with accuracy as a metric to judge the performance of a classification model can lead to a biased conclusion if the data is imbalanced. Therefore, the random forest model implements a confusion matrix to inform and evaluate how well the model performs. This confusion matrix compares the predicted values with the actual values in the model and uses them to analyse how the random forest performs on the data. Table 6 is included to provide a clear illustration for the interpretation of the confusion matrix.

	Actual crime	Actual no crime
Predicted crime	TP	FP
Predicted no crime	FN	TN

Table 6: Confusion matrix - illustration

A confusion matrix consists of four categories describing how many cases the model predicts correctly and incorrectly and what type of correct or incorrect prediction is made. When the result is True Positive (TP), the model correctly predicts that a crime could happen. The model incorrectly predicts where a crime could happen when it is False Positive (FP). Moreover, a True Negative (TN) result means that the model accurately predicts where a violent crime could not happen. The False Negative (FN) means that the model incorrectly predicted where a violent crime could not happen.

	Random forest confusion matrix				*Ntree = 500*
	Model 1 - 100x100	**1**	**0**	**Classification Accuracy**	**Classification Error**
	1	6194	1481	0.8070	0.1930
	0	1820	6465	0.7803	0.2197
P	**Classification**			**0.7932**	**0.2068**
R					
E	**Model 2 - 250x250**	**1**	**0**	**Classification Accuracy**	**Classification Error**
D	**1**	5507	1512	0.7846	0.2154
I	**0**	1639	5619	0.7742	0.2258
C	**Classification**			**0.7793**	**0.2207**
T					
E	**Model 3 - 500x500**	**1**	**0**	**Classification Accuracy**	**Classification Error**
D	**1**	4556	1384	0.7670	0.2330
	0	1319	4495	0.7731	0.2269
	Classification			**0.7700**	**0.2300**

Table 7: Random forest – confusion matrix

In Table 7, it is evident that there is a decreasing classification accuracy when the grid cell size on the map increases. First, in Model 1, there are 6194 cases of TP and 6465 cases of TN with a classification accuracy of 79.32 per cent. In Model 2, there are 1512 cases of FN and 1630 cases of FP and a classification error of 22.07 per cent. In Model 3, the TN value has a classification accuracy of 77.31 per cent, while there is a classification error for the TP value of 23.30 per cent. Overall, these findings suggest that the models have a high degree of accuracy in predicting both where a crime happens and where it does not. There is a 20 to 23 per cent chance for all models that a violent crime could not happen where it is predicted or could happen where it is not predicted, as well as there is a 77 to 79 per cent chance that the model can accurately predict where a crime could happen. Nevertheless, a more detailed analysis, including precision, recall, sensitivity, and specificity, is necessary to assess the models' overall performance more accurately.

Random forest analyses

Ntree = 500

Model 1 - 100x100		Model 2 - 250x250		Model 3 - 500x500	
F1-score	0.7896	**F1-score**	0.7776	**F1-score**	0.7712
Precision	0.8070	**Precision**	0.7846	**Precision**	0.7670
Recall	0.7729	**Recall**	0.7706	**Recall**	0.7755
Sensitivity	0.7729	**Sensitivity**	0.7706	**Sensitivity**	0.7755
Specificity	0.8136	**Specificity**	0.7880	**Specificity**	0.7646
Kappa	0.5864	**Kappa**	0.5586	**Kappa**	0.5401

Table 8: Random forest – results

Accounting for precision, recall, specificity, and sensitivity, the model can estimate how many of the positive results are truly positive and negative. Precision and recall are values that classify the true positive and false positive classes and the identification rate by type I and type II errors.

Equation 2 – Precision

$$Precision = \frac{TP}{TP + FP}$$

The precision of the random forest model is measured to determine the number of positive classification samples correctly identified and demonstrates the percentage of the relevant predicted results. For Model 1, 80.70 per cent of the class samples are correctly identified, whereas the percentage of the relevant predicted values decreases to 78.46 per cent in Model 2 and 76.70 per cent in Model 3 using Equation 2 to quantify the precision of the classification model.

Equation 3 – Recall

$$Recall = \frac{TP}{TP + FN}$$

Furthermore, recall measures the proportion of all values correctly classified by the random forest algorithm among all positive classes predicted or should have been predicted using Equation 3 to calculate the recall function for each model. Model 1 has an accuracy score of 77.29. Model 2 has an accuracy score of 77.06. Model 3 has an accuracy score of 77.55. These results suggest that a map with 500x500m grid cells performs slightly better than the other models in correctly identifying positive classes.

Equation 4 – Sensitivity

$$Sensitivity = \frac{1}{1 + \left(\frac{FN}{TP}\right)}$$

Like recall, sensitivity measures the proportion between the true positives and false negatives correctly identified in the model. The sensitivity is quantified using Equation 4, which shows that all three models are consistent with the recall since each model has identical values.

Equation 5 – Specificity

$$Specificity = \frac{1}{1 + \left(\frac{FP}{TN}\right)}$$

It is essential to consider the specificity metric when predicting on imbalanced data. The specificity describes the proportion of true negatives correctly predicted using Equation 5. When measuring the specificity of each model, Model 1 accurately predicts 81.36 per cent of the true negatives, while Model 2 and Model 3 correctly predict 78.80 per cent and 76.46 per cent, respectively. Overall, the random forest models are suitable for identifying where violent crimes could not happen since the models have a low false positive rate.

Equation 6 – F1-Score

$$F1 - Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} = \frac{2x\ Precision\ x\ Recall}{Precision + Recall}$$

While precision, recall, sensitivity, and specificity are important evaluation metrics for the model's performance and the reference to the percentage of the classifications correctly classified by the random forest algorithm, these predicted outcomes of the model can come at the cost of one another. After evaluating the predictive performance of the random forest model, the F1-score is applied as an assessment metric that further measures the model's accuracy by combining the precision and recall scores of the model. The F1-score is calculated using

Equation 6 and measures the harmonic mean of the predicted values. Utilising the F1-score is a more straightforward but comprehensive evaluation metric compared to the evaluation of the accuracy by itself. The F1-score simultaneously maximises the precision and recall scores which is used for classification and overall evaluations. In situations where the cost of false positives and negatives is high, the F1-score is especially important. It is essential because the F1-score can minimise the number of false predictions by ensuring that the model is accurately identifying the correctly predicted classifications.

The random forest Model 1 achieves the highest F1-score of 78.96 per cent, indicating a better balance between precision and recall, and therefore could be considered the best model for accurately predicting violent crimes in Oslo. Model 2 and Model 3 has a slightly lower score of 77.76 per cent and 77.12 per cent, respectively. These results indicate that when the number of grid cells increases, the model may become less effective in predicting violent crime events.

Random forest variable importance score

Ntree = 500

Model 1 - 100x100	**0**	**1**	**Mean Decrease Accuracy**	**Mean Decrease Gini**
Place of crime	33.6401	94.6679	100.1542	1486.0295
Footway	33.3871	75.9970	92.9335	907.3549
Forest	0.8171	82.8187	82.3439	521.0924
Public Building	-25.1145	76.4891	76.1613	835.4992
Time lag	85.0339	-35.8811	73.3222	364.4338

Model 2 - 250x250	**0**	**1**	**Mean Decrease Accuracy**	**Mean Decrease Gini**
Place of crime	18.8651	57.8267	62.1324	754.3195
Residential	19.7072	40.4214	47.1256	303.0892
Living street	6.7678	47.0556	45.7725	158.5840
Time lag	48.1032	-27.4289	44.7622	382.9001
Important roads	11.4722	41.3694	44.4528	74.4157

Model 3 - 500x500	**0**	**1**	**Mean Decrease Accuracy**	**Mean Decrease Gini**
Place of crime	18.1415	58.4157	66.2160	617.0663
Living street	7.2118	52.7879	55.2166	162.2412
Smaller local roads	8.7826	48.6253	54.2569	92.0939
Pedestrian street	28.7217	47.5175	53.5353	638.7496
Tertiary roads	6.4355	53.1776	52.6681	128.9138

**Sorted on mean decrease accuracy*

Table 9: Variable importance based on mean decrease accuracy

Equation 7 – Mean decrease accuracy

$$MDA(x) = \frac{accuracy\ of\ the\ model\ when\ feature\ (x)\ is\ not\ used}{accurcay\ of\ the\ model\ validation\ set\ when\ feature\ (x)\ is\ used}$$

To assess the variable importance score in the random forest models, Mean Decrease Accuracy (MDA) measures the model's performance by evaluating the accuracy with and without each added feature using the validation set. MDA determines the total decrease in accuracy achieved by each feature when the model is randomly arranged and highlights the impact on the model's predictive accuracy when removing a specific feature. In Table 9, the top 5 essential features of the random forest are quantified using Equation 7.

The MDA is used to calculate the relative importance of each feature in predicting crime. Based on their MDA scores, the five most significant features of predicting crime when the grid cell size is 100x100m are places of crime, time lag, footway, forest, and public buildings. For the second model, place of crime, residential, living street, time lag and important roads are the five most essential features to predict crime when the grid cell size is 250x250m. When the grid cell size on the Oslo map is 500x500m, places of crime, living streets, smaller local roads, pedestrian streets, and tertiary roads are the most influential predictors of violent crimes in Oslo. Appendix 2 includes a variable importance plot used to visualise the actual outcome of the random forest model by displaying how each feature is significant in classifying the data presented with descending importance. By looking at how the MDA suffers, it is possible to assess the importance of each feature for the successful classification of the random forest model. Furthermore, the MDA score suggests that the variable of the place of crime has a relatively significant impact on the performance of the model. The overall accuracy of the random forest model could decrease by approximately 100.15 units if place of crime was removed from Model 1. This finding is significantly different from place of crime in Model 2 and Model 3, whereas both models could decrease by 62 and 66 units if place of crime was removed from the analysis.

In summary, Model 1 with 100x100m grid cells is the best model to predict the spatiotemporal patterns of violent crimes in Oslo. This model is best because expanding the grid cell dimensions decreases the accuracy for the remaining models, which suggests that larger grid cells may impede the random forest model's ability to detect spatiotemporal patterns. The literature review argues that crimes are not randomly distributed in time, space, or society (Alves et al., 2018; Andresen, 2008; Brantingham et al., 2017; Newton and Felson, 2015;

Ratcliffe, 2010; Weisburd et al., 2016; Wortley and Townsley, 2017). The research findings from this thesis are consistent with previous studies, demonstrating that violent crimes in Oslo exhibit a spatiotemporal pattern characterised by the presence of hotspots and near-repeat offending.

Discussion

This section will analyse the study's main findings and explore the potential trade-offs and ethical implications associated with using predictive policing for the prevention of violent criminal behaviour. The application of the random forest model has proven effective in identifying significant criminogenic factors related to violent crimes in Oslo and in predicting their likely locations. While this study does not provide statistical evidence for the *causes* of violent crimes, it can offer insights into the factors that may influence or contribute to such behaviour. The primary objective of this research was to comprehend to what extent the integration of environmental criminology and supervised machine learning could enhance the accuracy of crime prediction while also being aware of potential implications of human-computer interaction. Thus, the following section is divided into three parts, each analysing the empirical evidence relevant to the present study, aiming to address the research questions. First, this discussion argues the essentiality of crime mapping for predictive policing and draws on the literature review to discuss why crime mapping can be necessary for crime prevention. Secondly, this thesis discusses whether machine learning can facilitate accurate crime predictions and assess the performance of the random forest models. Third, the discussion attempts to identify and examine significant considerations to reflect upon when employing predictive policing policies for crime prevention. Some of these implications include the need for precision in crime mapping, being aware of racial bias and type I and II errors that may follow when using predictive policing to forecast violent criminal behaviour. To summarise the main arguments, a section is included to explore the concept of AI as a public "good". Finally, this discussion will address potential limitations to the present study while embracing future research possibilities.

Why are crime prediction and mapping necessary?

Using crime mapping and crime prediction to identify spatial and temporal crime trends in a place, can further inform the development of crime prevention strategies to reduce future crime events. The literature suggests that measuring crime in the fourth dimension can contribute to predictive policing with valuable information on the physical, social, and economic characteristics that may influence the spatiotemporal patterns of violent criminal behaviour (Brantingham and Brantingham, 1991). Brantingham and Brantingham (1991) argued that failing to study crime in all four dimensions might distort the complete understanding of the initial reason for a crime. As they suggested, incorporating all, or at least two or more, dimensions for crime prediction can be crucial to account for the complex and multifaceted factors that influence criminal behaviour over time. By considering these dimensions when using spatial analysis, it can be critical for fully understanding the interplay between them to prevent crime. It can also facilitate the development of more efficient policies and crime prevention strategies that specifically targets crime generators or attractors, which can contribute to counteract violent crimes in society. The evolution of laws and changes in offenders' behaviour patterns over their lifetimes can highlight the importance of considering all dimensions in crime prediction rather than relying on a single data point (Mcdaniel and Pease, 2021b). Failing to account for specific dimensions can limit the ability to comprehensively understand why a crime happened in a specific location. While this research could not adhere to Brantingham and Brantingham's (1991) suggestion to include all four dimensions of crime, it can still contribute with valuable insights for predictive policing by arguing that spatial and temporal crime patterns are predictable, also when using a random forest algorithm. Based on the random forest models' high prediction accuracy in this study, it is reasonable to assume that predictive policing technologies can effectively contribute to deterring and reducing violent crimes in Oslo.

As previously discussed, identifying how people interact in specific environments can make it possible for officials to develop more effective solutions to prevent crime in space and time (Eck, 2003). Then, if offender-target interaction happens where capable guardians are incapacitated or absent, the offender may become more confident in committing a crime when the attached risks are reduced (Cornish and Clarke, 1987). Relating this offender-target interaction to Cohen and Felson's (1979) crime triangle, it is likely that when capable guardians are absent and the offender and target meet, it can potentially increase the likelihood of crime in a place. This study's results showed that violent crimes in Oslo could be predicted with up to 80 per cent accuracy and were often located within the inner city border of Oslo. From this result, it is possible to assume that Oslo's inner city, or the central business district, operates as a significant activity node where the target's and offender's routine activities regularly overlap. Ratcliffe (2010) notes that crime mapping can help identify spatial trends and contribute to a deeper understanding of the connection between geography and criminal opportunities. Therefore, incorporating environmental criminological theories and crime mapping can improve targeted crime prevention practices and inform predictive policing strategies by enhancing their effectiveness.

Furthermore, researching the spatiotemporal crime distribution can offer a holistic perspective on violent crimes and provide new insights that may contribute to enhancing predictive policing policies. Studies conducted by Brantingham and Brantingham (1993b), Groff and Lockwood (2014), and Xia et al. (2021) found that the distribution and patterns of crimes varied depending on specific crime types, the surrounding environment, and available opportunities. My study identified footways, pedestrian streets, living streets, important roads, minor local roads, tertiary roads, and forests as significant predictors of violent crimes in Oslo. Although this research did not establish causation between environmental factors and crime, the identified features align with previous findings indicating that offenders tend to commit violent crimes in areas related to their routine activities while travelling to and from activity nodes (Brantingham and Brantingham, 2008; Johnson, 2017). These, findings aligns with the previous research indicating that areas with explicit criminogenic characteristics and its proximity to non-residential facilities such as street segments, bars, schools, and public transit stops are features of significance for predicting violent crimes (Braga and Clarke, 2014; Brantingham et al., 2017; Deryol et al., 2016; Groff and Lockwood, 2014; Newton and Felson, 2015). Furthermore, my findings highlight potential environmental features that may serve as predictors for where violent crimes happen in Oslo. Hence, detecting environmental factors that could promote violent crimes can provide essential information for predictive policing, enabling the identification of high-risk areas more likely to experience violent crimes.

Understanding what can influence offenders to commit a violent crime at a certain location

While specific environmental factors can be considered criminogenic, investigations into the offender's decision-making process may help explain other significant factors for why an offender decides to commit a violent crime. The present study has introduced rational choice theory as one of its theoretical frameworks to illuminate how spatial characteristics may foster criminal behaviour in society by creating criminogenic opportunities. As mentioned, rational choice could explain up to 78 per cent of the likelihood of committing a crime (Weisburd and Piquero, 2008 in Sidebottom and Tilley, 2017), therefore, by understanding the potential decision-making process of offenders, it can be possible to gain new perspectives on the criminogenic cues in society that can trigger impulsive behaviour or strategic rationalisations. Additionally, rational choice theory can be used as a framework for preventing and deterring situational crimes by connecting the decision-making process to the immediate environment

(Cornish and Clarke, 1987). While there may be a combination of factors contributing to committing a crime, the widespread presence of opportunities and the desire for personal gain can motivate the offender to choose a specific target following a deliberate thought process (Brantingham et al., 2017; Collins and Loughran, 2017; Cornish and Clarke, 1986; Cornish and Clarke, 2017; Matsueda et al., 2006; Sidebottom and Tilley, 2017). Furthermore, viewing offenders as rational actors may lend support to the argument that crimes can be explained or anticipated based on the environment and its ability to shape the offender's decision, which could lead to more effective crime reduction strategies in a given area (Satz and Ferejohn, 1994; Sidebottom and Tilley, 2017). Then, law enforcement can use predictive policing to improve crime prevention strategies using rational choice theory and spatial crime analysis to establish where or when a potential offender will engage in criminal activity.

Building upon the rational choice theory, researchers contend that routine activities could be integral for describing violent crime events from a macro-perspective as an opportunistic process (Anselin et al., 2000; Felson and Clarke, 1998; Kondo et al., 2018; Miró, 2014; Ratcliffe, 2006). Therefore, applying routine activity theory as an additional theoretical framework when forecasting the location, timing, and quantity of violent crimes in an area can further contribute to advancing predictive policing by examining the interplay between routine activities, rational choice, and the offender's immediate environment. The concentration of people in specific criminogenic areas can increase the likelihood of criminal incidents when the crime triangle is completed by facilitating the crossing of the perpetrator and the target in time and space, potentially in locations where guardians are absent (Braga and Clarke, 2014). Thus, by identifying what factors can contribute to violent criminal incidents, law enforcement agencies can more effectively work to prevent or minimise criminal activity in a particular area by enhancing control measures or disrupting the formation of the crime triangle. Furthermore, Felson (2017) explains that routine activities can affect predatory crimes and points out that offenders depend on meeting the targets when they are more vulnerable to crimes, and when performing routine activities within a potential offender's activity or awareness space. Therefore, utilising routine activity theory as a framework in predictive policing can help explain where or what routines can influence crimes and can contribute to comprehending violent crime patterns related to space and time.

Zip's principle of least effort (1950 in Felson, 1987) and Felson's (1987) notion of lazy reasoning criminals, suggest offenders are more likely to commit crimes in familiar areas as part of their daily routine activities or while travelling to a destination where the offender can select targets based on minimal effort. The findings in my study support their argument that offenders are more likely to commit crimes en route to activities, as various road types are found to be significant predictors of violent crimes in Oslo. Similarly, this study also found evidence for spatiotemporal dependency in the crime distribution, suggesting patterns of near-repeat offending because the offender moves within a specific area where violent crimes repeatedly occur at nodes or on the connecting paths. In a previous statement, I argue that it is reasonable to view roads or paths as potential contributors to violent crimes based on previous research contending that criminal activity often occurs on paths connecting nodal points or routine activities (Brantingham and Brantingham, 2008; Johnson, 2017). Therefore, recognising tempting opportunities within the offender's awareness space may help reduce violent crimes by understanding the purpose of the crimes and target selection, particularly if the offender rarely ventures beyond familiar paths. Nevertheless, when offenders are forced to change locations, they might start casing new areas and familiarise themselves with new routines (Santos, 2017). In these situations, law enforcement can be better prepared by applying predictive policing to discover new trends more quickly and prevent future crimes by keeping law enforcement one step ahead of potential criminal activity.

Furthermore, Felson (1987) argues that offenders use lazy or 'most obvious' reasoning, thereby suggesting offenders have bounded rationality because they might overlook targets that yield more significant rewards by taking quick risks or because of laziness. If the environment facilitates crime by allowing the offender to blend into the ambient population, offenders can be more likely to take quick risks in places where they are less likely to arouse suspicion. Additionally, when quick risks are deemed suitable it may contribute to completing the crime triangle when capable guardians have reduced visibility or capacity for social control. The literature has indicated that violent criminal conduct may be more concentrated when the location of the crime coincides with routine activities close to activity nodes (Brantingham et al., 2017). The central business district, in particular, can function as a pivotal hub that connects various regions and people, leading to a significant flow of individuals passing through the area for routine activities. Thus, there is a possibility that crimes happening in the central business district are related to the activities and frequent flow of people throughout the day. This factor could exacerbate the concentration of criminal incidents in this location by making offending easier, allowing offenders to blend into the ambient population.

Figures 4, 5, and 6 show that most violent crimes are predicted to happen in Oslo's central business district, which may align with the Chicago school approach suggesting crimes are more likely to happen at the city centre. In contrast to the Chicago school, the present study reveals that crimes spread outwards in the city rather than diminishing as one moves away from the city centre. These findings may suggest that even though a crime can be perceived as a rational choice, they happen when offenders recognise criminal opportunities while performing routine activities and encountering suitable targets without capable guardians (Felson, 1986; Felson, 1987; Kondo et al., 2018). In this context, it is possible that Oslo's inner city facilitates violent crimes connected to rational choice and routine activities due to the clustering of businesses, leisure destinations, and a persistent flow of people in the city's centre. Consequently, understanding the structure of routine activities can make it possible to determine the frequency of crimes and predict which areas may be more exposed to violent criminal behaviour. It can also be possible to determine what areas work as crime generators or attractors (Brantingham et al., 2017). In summary, analysing the movement of people and connecting it to routine activities or rational choice theory might contribute to valuable analyses connecting areas with an increased likelihood of crimes (Kaufmann et al., 2019).

Besides routine daytime activities, the nightlife in Oslo can be found in the central business district. Similarly, violent crimes, in particular, are more likely to happen at nighttime (Brantingham and Brantingham, 1993a). Some studies have reported that violent criminal behaviour could increase in proximity to bars, which can be linked to alcohol consumption or illegal substance use (Abrams, 2021; Day et al., 2012; Eck and Weisburd, 2015; Gerell et al., 2022). This increase in violent crimes can also happen because the potential offender recognises nearby opportunities when there is a lack of social control (Braga and Clarke, 2014; Felson and Clarke, 1998; Newton and Felson, 2015; Ratcliffe, 2012). My study identified that 45 per cent of all registered violent crimes in Oslo happened between 00:00 and 04:00 am, and 50 per cent of all violent crimes in Oslo were registered as assaults, threats, or reckless behaviour. These identified violent crime types are crimes that often show aggressive tendencies and might be connected to illegal substance use or excessive alcohol consumption (Rossow and Norström, 2012). These findings can support previous crime literature suggesting violent crimes increase in the evening and that they might be connected to nighttime routine activities. As an illustration, Rossow and Norström's (2012) research revealed that nighttime assaults in the city centre increased with extended closing times. They found that bar closing times in 18 Norwegian cities were associated with a statistically significant increase in violent crimes, accounting for approximately 16 per cent of the increased crimes (Rossow and Norström, 2012).

It is possible to assume that violent crimes may increase in proximity to bars because of the psychological effect that promotes risk-taking behaviour and the disinhibition effect that may result in violent criminal conduct due to increased aggressive behaviour and willingness to take risks (Block and Block, 1995). To support the claim that assaults, threats, and stalking behaviour can be tied to routine activities at night, a study by Kooistra (2021) found that substance abuse could increase impulsive behaviour, impair self-control, and cause a decrease in the capacity for legal compliance. Suppose offenders develop aggressive behaviour and lose the ability to comply with the law when consuming alcohol or illegal substances. In these cases, it could be argued that low social control may further increase the likelihood of violent crimes. Additionally, when there is a large concentration of people engaged in nightlife activities, there may be a diminished capacity for informal social control, as limited visibility hinders the ability of bystanders to monitor and intervene in potentially criminal situations. Correspondingly, Townsley (2017) argues that when offender decision-making is integrated with routine activities in a low visibility setting, it provides the offender with the opportunity and likelihood of succeeding when committing a crime, without arousing suspicion, as they can blend inconspicuously into the ambient population. The ability to blend into the ambient population in low visibility settings might explain why this study reported that 45 per cent of all violent crimes in Oslo occurred during the weekends and at nighttime.

Interestingly, the findings display that reckless behaviour and stalking increased by 50 per cent from 2016 to 2020. This increase may suggest that the offender moves with the target or that the target moves in the offender's awareness space. Therefore, understanding the target and offender's daily movement patterns may be crucial for implementing effective crime prevention strategies in policing to reduce violent crimes in Oslo. Additionally, it may be imperative to identify the underlying factors that generate, attract, or influence violent crime incidents in a specific area. This knowledge can be applied in predictive policing to map and understand violent criminal activity in areas with similar characteristics. Previous research has suggested that crimes clusters near an offender's activity and awareness space and may concentrate around activity nodes, particularly if they coincide with the routine activities of potential targets (Brantingham et al., 2017; Ratcliffe, 2012; Townsley, 2017). The research findings agree with this notion, as most violent crimes were predicted in the inner city limit of Oslo, where there is a constant flow of people due to routine activities associated with leisure and business. Furthermore, this argument is supported by the literature, which found that potential offenders can be attracted to areas with frequent movement, routine activities, and criminal opportunities (Braga and Clarke, 2014; Brantingham et al., 2017).

Furthermore, it was argued that crime patterns and routine activities are fundamental for developing effective policing strategies (Brantingham et al., 2017). This understanding involves identifying nodes and areas where people may be forced into constrained movement patterns and recognising that offenders travel with regular movement patterns depending on time and space. Since it was argued that urban characteristics could influence crime patterns (Alves et al., 2018; Ratcliffe, 2006), it is plausible that mapping the spatiotemporal changes in these patterns and identifying the criminogenic features that may attract or generate violent crimes, can contribute to predicting where and when violent crimes are more likely to increase. Moreover, the descriptive analysis demonstrated that the frequency of violent crimes would increase in the summer and decrease in the winter. This descriptive analysis indicates that crime increase when the temperature changes and when there are more people outside, gathering at activity nodes. Previous studies have suggested that temperature might affect violent crimes in Sweden and the USA (Ranson, 2014; Uittenbogaard and Ceccato, 2014). Contrastingly, this study's random forest model, similar to Hart et al. (2019) using generalised additive models, found that temperature had little to no impact on violent crime distribution in Oslo as the effects were microscopic. While using temperature is not enough to affect violent crime patterns in Oslo in this study, it does not necessarily mean it is insignificant. Uittenbogaard and Ceccato (2014) argue that the extreme differences in weather conditions in Scandinavian countries are likely to impact routine activities and criminal opportunities. Hence, it is possible to assume that this is similar in a Nowegian context although the weather features in itself was not significant. However, the seasonal patterns may already be accounted for in the violent crime patterns.

Consequently, the influence of weather on the data may not be visible and it may be more appropriate to focus on temporal crime patterns rather than seasonal patterns when attempting to predict violent crimes in Oslo. Almanie et al. (2015) found that crimes were likely to peak on Wednesdays and at the weekends in Denver and Los Angeles, while my study revealed that crime peaked on Tuesdays and at weekends in Oslo, which is a slight deviation from Almanie et al. (2015) findings, albeit the difference is minor. These findings imply that, unlike weather data, knowing the temporal trends of violent crime distribution can help with resource allocation and developing predictive policing policies to ensure public safety when crime rates are predicted to increase.

This study found that if a crime occurred in a particular location the week before, it was more likely to happen again in the same area, thereby suggesting that something in the area contributes to criminal behaviour, whether due to routine activities or criminogenic features. These findings indicate a spatiotemporal dependency in the data. Therefore, mapping violent criminal behaviour can increase our understanding of the environmental backcloth by considering the complex features of an area and the offender's criminal pattern. By analysing the environmental backcloth and activity movement of violent crimes, it is possible to gain insight into features that may contribute to violent criminal activity (Deryol et al., 2016). As mentioned, the current study found that 45 per cent of all violent crimes happened at night or in the weekends, typically within Oslo's inner city limit, where people are forced into a specific movement pattern following routine activities. Additionally, my study found a connection between violent crimes and different geographical features, such as roads and public buildings. These findings highlight the importance of understanding an area's environmental features and routine activities in predicting and preventing crime. To further enhance predictive policing, law enforcement can use knowledge from spatial crime mapping to identify and monitor environmental features associated with violent criminal behaviour.

Crime prevention through environmental design

As established, violent crimes tend to concentrate in areas that connect routine activities (Brantingham et al., 2017). Consequently, it was suggested that crimes occur near activity nodes or along the paths connecting these nodes (Brantingham et al., 2017). My study identified a variety of roads and paths significant for predicting the location of crimes, which implies that offenders may plan their criminal activities while travelling to and from their routine destinations or other activity nodes. For law enforcement, policymakers, and urban planners, these findings can indicate that criminal hotspots are associated with the spatial setting where potential offenders and targets interact, often with a mix of substances or close to an easy escape route (Bruinsma and Johnson, 2018). Therefore, using crime mapping to identify the spatial distribution of crime within a city can help locate areas more susceptible to violent criminal conduct, and to understand essential urban features that may contribute or encourage criminal activity. Felson and Boba (2010) claimed that law enforcement should understand what contributes to the crime problem to be able to prevent repeat offending and similar crimes elsewhere. With the advancement of spatial crime research, understanding the environment's direct impact on crimes can be fundamental for enhancing predictive policing policies. By pinpointing nodal areas where both the offender and target routine activities intersect, it may be possible to introduce new policies targeted at preventing or reducing the likelihood of criminal behaviour by manipulating the physical space where crimes are predicted to happen (Ferguson, 2017; Jeffery, 1969; Jeffery, 1976). While removing criminogenic features from urban spaces may reduce the appeal of the areas as crime sites and potentially lead offenders to relocate to other locations, crime prediction tools may detect and anticipate changes in the crime patterns, helping law enforcement to adjust their strategies accordingly and prevent criminal activity from spreading to new areas.

Furthermore, according to Block and Block (1995), Gerell et al. (2022), and Rossow and Norström (2012), bar closing times could increase nighttime criminal activity in Norway in bar areas, potentially because simultaneous bar closing times can generate a crowd effect that can cause further disruption and conflict in the specific area and adjacent areas. Although the current study did not include bars in the analysis, the data suggests that the rise in crime during evenings and weekends could be associated with nightlife activities and increased behaviour in the city centre. These arguments align with my research, as crimes were found more likely to increase during the weekends and at nighttime, often in the inner city, indicating a spatiotemporal dependency on crime. Similarly, if closing times generate a crowd effect, it can facilitate the interaction between offenders and potential targets in public spaces where capable guardians cannot act as crime preventers. Therefore, regulating bar locations close to residential blocks and avoiding bar zones or strips, as suggested by Roncek and Bell (1981), could be an effective measure to reduce the risk of violent crimes in such areas. Moreover, public policies involving closing times or targeted at reducing people in the streets can contribute to minimise the likelihood of the crowd effect associated with violent behaviour. Based on my findings, it is clear that predicted violent crimes are more frequent within Oslo's inner city limits. These findings could imply that completing the crime triangle is more likely to happen when individuals are confined to a space where interaction between the target and offender is unavoidable. To avert violent crimes, crime prevention through environmental design may be possible by manipulating the social space in areas with bars to avoid the crowd effect, which is believed to contribute to an increase in violent crimes.

Predicted crime areas may have a vast spatial extent, making it impossible for law enforcement to be present everywhere simultaneously. Therefore, relying on capable guardians to safeguard society against criminal activities can be fundamental if bystanders can reduce crime by implementing informal social control by being present or visible in society (Felson, 1986). With improved social control, the risk of offending may increase because the risks outweigh the benefits of committing a crime (Cohen and Felson, 1979; Felson and Boba, 2010; Miró, 2014). Moreover, manipulating the social space to prevent violent crimes can be effective for re-establishing human contact by encouraging collective efficacy, social cohesion, and social control in a community. By strengthening the sense of collective responsibility, individuals can better work together as guardians to deter potential offenders, making offending more challenging (Andersen et al., 2021; Andresen, 2010; Kubrin and Weitzer, 2003; Weisburd et al., 2016). According to Newman (1972 in Andresen, 2010), crime prevention through environmental design can limit or prevent crime at place by creating a defensible space that can reduce crime overall by creating an environment that defends itself. Implementing a natural defence mechanism when designing urban space, such as open places, clear visibility, and well-maintained areas, while ensuring people are not constrained in an area, can reduce the need for over-policing and prevent crime through the natural area (Andresen, 2010; Mcdaniel and Pease, 2021b).

According to Mohler et al. (2018), crime detection relies on local residents reporting incidents. Hence, fostering social cohesion through promoting community engagement may become critical for establishing effective social control mechanisms. Such measures can help alleviate the sense of over-policing and marginalisation while simultaneously enhancing collective efficacy within the community (Andersen et al., 2021; Kubrin and Weitzer, 2003). Moreover, by creating an environment that naturally promotes social cohesion and collective efficacy, it might strengthen community bonds and contribute to effective crime prevention efforts through manipulation of the social space and urban design, foster human interaction by inspiring social cohesion and collective efficacy (Jefferey, 1969). A socially disorganised area lacking social cohesion renders guardians ineffective since they are not contributing to community protection. The literature suggests that social disorganisation can reduce the residents' sense of solidarity and community, resulting in less motivation to address community issues or maintain a safe environment (Kubrin and Weitzer, 2003). Additionally, without collective efficacy, residents are less likely to take responsibility (Andresen et al., 2010). Henceforth, residents may become bystanders who unconsciously trigger the crime cycle by breaking down the community, resulting in deterioration and turning the area into a crime attractor and hotspot (Braga and Clarke, 2014). My study found that public buildings and residential areas significantly predict violent criminal behaviour. This finding may suggest that social disorganisation in an area can contribute to increased violent crime activity in some areas, possibly due to the lack of collective efficacy or social cohesion. One approach that policymakers and urban planners may consider is to use geographical analysis to understand better the spatial and temporal patterns of crime, which could inform the architecture of public spaces and the placement of connecting points to increase guardianship and promote social cohesion. This approach may help to improve collective efficacy and enhance vigilance among potential guardians, which could contribute to crime prevention through environmental design.

Using supervised machine learning to predict spatiotemporal crime patterns

Integrating advanced technologies into predictive policing can help facilitate proactive measures to prevent future criminal activity. These technologies can enable researchers, law enforcement, and policymakers to identify and understand what contributes to crime patterns and hotspots in society, primarily because crime pattern studies can provide valuable insights into the relationship between the environment and criminal events (Oh et al., 2021). Insights into the distribution of violent crimes using AI can enhance the understanding of crimes at place by expanding the policing landscape (Anselin et al., 2000; Weisburd et al., 2016). This technology can have the potential to pre-empt violent crime situations by precisely and efficiently recognising criminal activity patterns. This thesis suggests that AI through supervised machine learning can be used in predictive policing to insinuate where and when crimes are more likely to happen and where to deploy the police to prevent violent crimes in Oslo. Previous studies in predictive policing have often used linear and logistic regression models to measure the probabilities or statistical relationships between spatiotemporal crime patterns and environmental factors (Berk and Bleich, 2013; Deryol et al., 2016; Kounadi et al., 2020; Thomas and Drawve, 2018). The present study employed a random forest model to predict the spatiotemporal distribution of violent crime patterns in Oslo. As such, it could not assess the correlation between environmental characteristics and violent crimes. However, by incorporating grid cell maps with environmental features into the random forest model, the present research successfully predicted potential locations of violent crimes with up to 80 per cent accuracy. This accuracy made it possible to establish urban indicators that could be significant for accurate crime predictions. Additionally, it demonstrates that the use of more advanced statistical tools to predict crime locations can benefit predictive policing and predictive policing policies.

Crime prediction can be challenging, particularly if the data is scattered with no apparent patterns (Wang et al., 2019). According to Oh et al. (2021), supervised machine learning models could provide accurate predictions by implementing a learning-based forecasting algorithm to predict spatiotemporal crime trends. This study's random forest model could accurately predict crime and pick up weekly temporal patterns, which makes it possible to assume that the random forest models can identify crime generators or attractors by recognising the spatiotemporal changes in violent crime trends. The crime literature suggests that offenders travel with regular movement patterns, varying depending on time and surrounding situations (Ratcliffe, 2006). Machine learning algorithms can efficiently detect both typical and atypical violent crime patterns, facilitating the identification of changes in their distribution. If offenders are rational and driven by greater rewards or decreased risks, the potential offenders may move towards areas outside their routine activities and familiar paths to achieve higher rewards with reduced risks (Brantingham et al., 2017). By continually monitoring and analysing crime data, law enforcement can identify emerging crime hotspots and take proactive measures to prevent criminal activity from taking hold in new areas. Therefore, identifying changes in crime patterns can be critical for implementing effective crime prevention strategies and mitigating the risk of criminal activity in new or unexpected areas.

In the literature, Kaufmann et al. (2019) noted that crime patterns could be a universal driver for predictive policing because patterns may show some regularity over time. Therefore, it can be substantial to implement algorithmic technology to detect the spatial change in violent crime patterns. Although machine learning technology can detect new and changing crime patterns, my research suggests that grid cells should be at most 100x100m in size. Accordingly, the random forest model using a 100x100m grid cell dimension outperformed the other models in predicting spatial crime patterns. Therefore, increasing the grid cell size could result in more information being contained within each grid. Then, the increased amount of characteristics within each grid can make it more difficult for the other models to identify the violent crime patterns, as all grids become more homogeneous when considering the characteristics included in the model.

How can using machine learning contribute to crime prevention?

Supervised machine learning through random forest models can be applied as a statistical tool to accurately predict where and when a violent crime would happen in Oslo in four out of five cases. These results implies that random forest used for crime analysis exhibit high prediction accuracy, surpassing the accuracy of chance-based crime prediction. Therefore, a random forest model may have the potential as a learning-based model to improve current policies and procedures to ensure fairness in predictive policing. The findings of the present study indicate that the implementation of random forest and GIS can effectively predict changes in violent crime patterns over time, successfully identify regions at high risk for criminal activity, and can be trained to detect patterns when the algorithm receives new data and feedback. Findings in this study imply that integrating GIS technology and machine learning algorithms for predictive policing can lead to more accurate predictions by linking geographical data, crime data, and other relevant factors influencing violent crimes. Similarly, implementing machine learning algorithms can be important for crime prediction, and can contribute to identify significant characteristics associated with criminal behaviour. Thus, this research agrees with Ratcliffe (2004) that using GIS and machine learning may advance the field of predictive policing and crime prevention.

Furthermore, it has been established that random forest models and GIS are effective for accurately predicting the spatiotemporal distribution of violent crimes in Oslo. Scholars argue that previous criminological theories have excessively focussed on single crime events (Brantingham et al., 2017; Felson, 2017; Weisburd et al., 2016). Thus, incorporating the fourth crime dimension in analysing violent crimes using machine learning for predictive policing can provide additional insights and knowledge valuable for law enforcement and policymakers. Moreover, using machine learning technology to monitor and locate crimes can contribute to improving patrol planning and resource allocations (Araújo et al., 2018). By taking advantage of the possibilities that machine learning can contribute to environmental criminology, predictive policing, and spatial crime analysis, it may be possible to use these resources more efficiently. Employing machine learning as a tool for predictive policing can provide valuable insights and improve the ability to predict and prevent crimes by highlighting areas more susceptible to criminal activity and linking them with environmental factors making officers more conscious of when and where a crime may occur.

My study found a moderate agreement (Kappa value of 0.59) between the predicted and actual outcomes for the random forest Model 1, which utilised 100x100m grid cells to predict violent crimes. These findings suggest that the model's predictions are somewhat reliable and consistent, but there is still a possibility of misclassification. While the Kappa value indicates a moderate level of agreement that a random forest model can predict better than chance, further investigations are necessary to determine the practical effectiveness of the random forest model in criminological applications. Additionally, Mcdaniel and Pease (2021a) notice that if the algorithm is designed for a specific purpose, such as forecasting the probability of a violent crime, it will not possess the capability to perform beyond its intended function. Therefore, this moderate level of agreement indicates that while AI and learning-based models can outperform random chance, trust in the computer-based model should be exercised with caution.

Because AI through Machine learning models is incapable of human-level principled analysis *yet*, this technology may contribute to more ambiguity if not handled appropriately (Mcdaniel and Pease, 2021b). Consequently, the reluctance to embrace complex technology may dissuade individuals from adopting more advanced statistical models even when it has the potential to enrich predictive policing by offering valuable insights into spatial crime trends (Berk, 2013; Chan, 2021). Moreover, Mcdaniel and Pease (2021a) argue that when police devise strategies and actions based on an output from an algorithm without understanding the causation, it could have devastating outcomes for both communities and individuals. Therefore, it can be fundamental that the technology is adequately understood before applying it in the real world and making decisions based on its results.

Furthermore, implementing new policies and recommendations for predictive policing based on data acquired through spatial crime mapping relies on neutral data with accurate georeferencing (Ratcliffe, 2004). Failing to achieve the minimum hit rate may, according to Ratcliffe (2004), lead to imprecise geocoding, resulting in data uncertainty. Thus, training officers and raising awareness of the potential consequences of inaccurately registering data can be crucial. An unawareness of system errors and potential consequences of inaccurate data registration is here understood as the Modifiable Areal Unit Problem (MAUP), highlighting that inexperienced users may occasionally and unknowingly map data points inaccurately, resulting in less reliable statistical analyses of spatial and temporal crimes (Ratcliffe, 2004). According to Johnson (2017), even a minor modification to the spatial data can shift the grids and affect the observed patterns. Therefore, mapping errors can reduce the reliability of statistical analysis and have significant repercussions for predictive policing policies and strategies (Johnson, 2017). By integrating predictive policing into officer training and giving it more emphasis can enhance the understanding of why precise geocoding is fundamental and contribute to improve the reliability and validity of spatial crime data. Raising awareness of the MAUP can help police patrols understand the significance of accurately registering crimes at their actual location, rather than in the patrol car, at neighbouring addresses, or elsewhere. It is also possible that this awareness can improve officers' ability to prevent crime by recognising spatial features that may influence criminal activity. In some circumstances, law enforcement may face difficulties in recording a precise location, such as incidents occurring in regions lacking distinct addresses, for instance, parks, forests, or vast areas. For example, the Oslo central station covers a large area within the city's central business area. Figure 4 shows a vacant grid cell next to a red grid cell, suggesting that a building or address extends over several grids. The empty grid cell implies that the MAUP could appear using smaller maps, such as 100x100m.

Finding the right balance between type I and type II errors

While predictive policing technology can help reduce violent crimes, it should be used cautiously and not relied upon exclusively. For instance, which mistake is more detrimental: sending patrols to areas where violent crimes did not happen[17], or having unpatrolled areas where violent crimes did happen[18]? To determine the optimal trade-off between type I and II errors, this thesis has examined the performance of the random forest algorithm in predicting violent crimes at three distinct levels. The most precise random forest model, which used 100x100m grid cells, had an overall accuracy of 79 per cent but generated false positive and false negative rates of 19 and 22 per cent, respectively, when predicting violent crime locations in Oslo. These results indicate that the model incorrectly predicts one out of five crime locations. Specifically, the higher false negative rate suggests that the model was more likely to predict that violent crimes would not occur in an area where they did. These findings can have important implications for the effectiveness of predictive policing and can emphasise the need for cautiousness when using AI-based crime prediction.

[17] Type I – false-positive

[18] Type II – false-negative

Furthermore, I have argued that using advanced technology for predictive policing necessitates adequate understanding, training, and a focus on reducing bias in data interpretation. Understanding how or why the algorithm produces its output is essential for detecting possible systemic bias in the data, despite the black box problem associated with the machine learning algorithm. This understanding is important for recognising potential bias or incorrect predictions of crime locations in both machine algorithms and human decision-making and can enhance the ability to identify and mitigate type I or II errors in predictive policing. While the ultimate goal is to prevent violent crimes by allocating resources to high-risk areas, it is essential to consider what areas the machine has predicted to avoid under or over-policing areas (Brantingham et al., 2018; Kaufmann et al., 2019; Richardson et al., 2019). Using random forest models in this analysis confirmed that there are going to be cases of incorrect predictions. Thus, providing evidence that the machine may not be able to make every decision by itself regarding where resources should be allocated. In this case, *knowledge-based policing* may contribute with pre-existing knowledge on what areas are more likely to experience crime to limit type I and II errors by dispatching patrols to areas with wrong predictions. Knowledge-based policing, in this thesis, is defined as using personal experiences instead of, or as a supplement to, the information generated by predictive technologies (Gundhus, 2012).

Violent crimes may differ from other types of crimes due to their potential for severe harm, and therefore, in some cases, it may be better to combine knowledge-based policing with machine-based decision-making to justify increased police presence in an area where it is believed that violent crimes may occur. However, striking the right balance is necessary to mitigate the harm caused by both violent crimes and excessive policing practices. By considering the potential consequences, such as excessive resource allocation and the potential for marginalisation of over-policed areas, it may be possible to implement this technology more fairly and accurately. While an increased police presence in a high-risk area may seem preventive, it may also lead to unfair apprehensions or targeting, biased data, social disorganisation, or community alienation (Newburn, 2011). Consequently, increased policing or a perception of constant surveillance may inadvertently contribute to social deterioration and disorganisation due to prediction errors (Hamilton, 2021). Then, these unintended outcomes of prediction errors or biased decisions can result in an increase in crime and a decrease in the overall feeling of safety. For areas suffering from type I errors, over-policing can lead to the neglect of areas where crime happens, resulting in a waste of resources and a lack of comprehensive crime prevention efforts. For areas suffering from type II errors, offenders may perceive the overlooked area as a low-risk area, potentially leading to an increase in criminal activities by functioning as a crime attractor. Similarly, it may reduce the feeling of safety if some areas are under-policed. This consideration of type I and II errors is necessary for the ongoing debate surrounding the implementation of predictive technologies. Thus, addressing the potential biases and limitations of these systems to ensure their fair and effective application may be essential. A practical example of under or over-policing phenomenon can be seen in the crime prediction maps in Figure 4, 5, and 6 since the predicted grid cell maps of Oslo reveal a higher occurrence of crime on the east compared to the west side. While previous arguments have pointed to social inequalities as a potential factor in this trend (Bakken, 2018; Glomseth and Aarset, 2022), it is important not to overlook the occurrence of crime in the west simply because there might be a higher likelihood of violent crime on the east side or within Oslo's inner city limits.

Avoiding pitfalls in predictive policing for crime prevention

As academics, law enforcement, policymakers, and other stakeholders, it is imperative to keep in mind that the use of AI to forecast the outcome or probability of violent crimes can impact individuals and communities where an increase in policing activity may have unintended negative consequences.

"Real decisions are being made affecting real people".

(Berk and Bleich, 2013: 515)

Considering Berk and Bleich's (2013: 515) statement that real decisions can affect real people, it proves the necessity to have precise data, models, and a team adequately trained to apply and analyse statistical findings effectively and ensure proper data collection to minimise type I and type II errors. Additionally, it can be crucial to comprehend the interplay between geography, criminal activity, and opportunity to inform targeted crime prevention practices. Ignoring these considerations may result in a failure to fully understand the underlying causes, locations, and timing of crimes. Although an 80 per cent accuracy for predicting the location of violent crimes is an improvement over random chance, there is still a 20 per cent chance of misprediction. For minor crimes, such as disorderly conduct, where the harm is typically limited, the absence of police presence may not have too serious consequences. However, in cases of more severe crimes, like armed robberies or aggravated assaults, the police should be present, nearby, or able to provide an adequate response more effectively. Similarly, using predictive policing to allocate resources to areas where crimes were predicted but did not happen can result in over-policing areas, which may exacerbate existing stigmas and biases towards residents in these areas. Over-policing can result in increased feelings of surveillance, stigmatisation, and mistrust, potentially leading to a negative feedback loop of more policing and further marginalisation (Lanestedt, 2016). Thus, relying on AI models' predicted outcomes to guide resource allocation for crime prevention can lead to unintended consequences because the computer may not always accurately predict the outcome.

The need for accurate and representative data in predictive policing

With the evolution of technology's complexity, there is a growing necessity for research on how data-enabled risk assessment tools can inform human decision-making (Babuta and Oswald, 2021). Given the likelihood of machine learning models mispredicting one in five cases, ensuring the accuracy of the input data before dispatching patrols to predicted crime areas is crucial. To certify that the predictions are accurate and appropriate, the researcher must comprehensively understand the model's nature, complexity, and statistical interpretation (Berk and Bleich, 2013). More specifically, the black box of AI technology can further intensify the risk of misinterpretation when there is inadequate knowledge of how to operate and interpret the output data due to the indecipherability of the models and computational decision-making (Pasquale, 2015 in Sandhu and Fussey, 2021). Providing adequate training and understanding of the technology used to predict crime can be crucial for ensuring transparency and reducing potential bias. Without adequate training or a failure to acknowledge the significance of precise data registration, the MAUP can lead to less reliable statistics, shifting the observed patterns and potentially resulting in type I or II errors. Such errors, as discussed, may lead to dispatching patrols to areas where the computer made incorrect predictions. If the algorithmic decision-making does not represent actual criminal activity, sending patrols to the wrong location based on partial data can increase the risk of reinforcing existing bias and potentially discriminating against specific areas or individuals associated with these areas.

While implementing predictive policing technology to patrol areas with a higher probability of crime can disrupt criminal opportunities, it is essential to note that police practices are still susceptible to biased assessments and decision-making. Therefore, when discussing implementing predictive policing technology in policing, it is crucial to remember that the neutrality of crime data depends on those who gathers and analyses it (Clavell, 2018). While crime mapping using AI technology may seem objective, there is a chance that some areas, or a specific group of people, are under- or overrepresented in the data (Chan, 2021; Mcdaniel and Pease, 2021b). Therefore, it is necessary to implement policing practices with caution, endorsing transparency and fairness to build public trust, which is fundamental for effective policing. Subjective determinations of where, when, and whom to police can position the police as gatekeepers to the criminal justice system (Sandhu and Fussey, 2021). This gatekeeping role may lead to the potential for biased practices, such as subjectively deciding where to locate patrols, whom to stop and search and whether to label an incident a crime. Consequently, police interventions can result in unfair treatment based on existing biases in the data, leading to unlawful or flawed policing practices (Richardson et al., 2019). These unfair, or biased, practices pose a severe risk of unjustified profiling based on religious, ethnic, or socioeconomic features, and can skew or systematically bias the data further, leading to an environment where the data is no longer neutral, and crime mapping is no longer representative (Clavell, 2018). Hence, ensuring transparency and providing adequate training becomes imperative for the effective and ethical use of predictive policing technology.

The balance between objectivity and subjectivity

The selective allocation of resources can introduce a systematic error in the data analysis and compromise the overall accuracy and effectiveness of predictive policing strategies. Deploying police resources to high-risk areas, particularly socially disorganised areas, may potentially distort or skew the results due to inherent biases in the data. On one hand, concentrating police presence in these areas may lead to accurate crime predictions. However, it also introduces the possibility of systematic errors, as the presence of police might generate crime incidents that would not have occurred in their absence, or neglect areas where crimes actually occur, as patrols are directed towards areas with lower crime rates based on knowledge-based policing decisions. The complexity of balancing objectivity and subjectivity highlights the challenges and potential trade-offs associated with resource allocation guided by predictive models. Nevertheless, it is important to acknowledge the potential existence of a higher frequency of criminal activity in a predicted crime area while also recognising and addressing the possible influence of bias.

When implementing predictive policing technology in real-world scenarios, an over-reliance on or insufficient understanding, evaluation, or acceptance of the technologies can lead to miscarriages of justice. This statement might hold true even for individuals with a high level of knowledge or expertise in policing technology. Careful assessment and critical examination of these technologies are crucial to ensure their appropriate and ethical use. For this reason, Mcdaniel and Pease (2021a) stress the necessity of proper training to ensure that the police comprehend the technology and results used for predictive policing. As Kaufmann et al. (2019) suggested in their paper, pattern-based crime predictions might reinforce certain policing cultures, shaping the way officers think about offenders and criminal activities. Consequently, officers patrolling an area may become more focussed on searching for crimes rather than actively preventing them. This emphasis on apprehending offenders can create a feedback loop, impairing officers' objective assessment of potential individuals in crime hotspots identified by the machine (Brantingham et al., 2018; Kaufmann et al., 2019; Richardson et al., 2019). Biased assessments for predicted crime areas may be further reinforced by officers' subjective knowledge or experience deciding that crimes are more likely to happen in the area. Accordingly, failure to objectively reflect on a situation, whether based on personal experience or computer-generated crime predictions, can lead to a heightened state of alertness when policing potential crime areas, as officers anticipate the possibility of criminal activities.

Furthermore, considering Kaufmann et al. (2019) argument that the data guides police action towards biased and concealed patterns triggering a cycle of crimes registered to a place, the placement of officers in areas where a violent crime is predicted may heighten the likelihood of apprehending individuals based on impulsive or intuitive judgements which are attributed to the officers' anticipation of criminal activity (Richardson et al., 2019). Triggering the feedback loop can have negative effects on predictive policing because excessively focussing on crime in specific locations due to biased assessments from knowledge-based policing may result in neglecting other areas with similar likelihoods of criminal activity. Consequently, Brantingham and Brantingham (1991) discuss more severe crimes may be overlooked or underestimated due to biased assumptions that associate a higher likelihood of crimes with specific criminogenic cues. Prioritising and patrolling biased anticipated crime locations over actual crime locations can lead to type I and II errors, as it fails to align with the true crime patterns. In similar cases, when officers patrol areas where the anticipation of violent crime prevails, it may significantly impact their judgement as they become predisposed to expecting criminal behaviour from individuals associated with high-risk crime areas. This phenomenon entails what Wacquant et al. (2014) refer to as territorial stigmatisation, where certain areas, neighbourhoods, or individuals associated with these places are stigmatised and marginalised due to their perceived association with criminality.

In the past, social control has relied on capable guardians to protect the community against criminal activities (Cohen and Felson, 1979; Felson and Boba, 2010; Miró, 2014). Because predicted crime areas may have an immense spatial extent, law enforcement may not be able to police or be present everywhere at the same time. Therefore, predictive policing technology could be imperative for prioritising which areas are more detrimental to patrol and at what time. However, as previously established, the machine might be incorrect in one out of every five cases of predicted violent crimes, making it difficult to determine when or where the predictive technology has made a mistake. While most cases are likely to be accurately predicted, it may be necessary to supplement and inform the decision about resource allocation with knowledge-based policing. Supplementing predictive policing technology with pre-existing knowledge may reduce the overall likelihood of type I and II errors because the decision incorporates contextual information and subjective insights that cannot be captured solely through data-driven algorithms. Nevertheless, it can be necessary to recognise that knowledge-based policing may introduce subjective elements based on individual experiences and opinions, which can potentially impact the objectivity of predictions. While subjectivity can provide additional insights for the decision-making process regarding resource allocation, it is important to acknowledge the potential for unfair targeting of individuals in a specific area. This targeting has the potential to exacerbate stigma within targeted or over-policed areas, further perpetuating social inequalities and biases thereby creating a suspect population (Newburn, 2011).

Impacts of policing decisions

Whether the data is systematically biased, its interpretation can be influenced by subjective decisions regarding the location and timing of policing efforts. If internalised bias influences the decision-making process, and if it aligns with the predicted outcome of the data, it is possible that some areas are more likely to be over-policed due to the expectations of violent crimes (Moravec, 2019 in Mcdaniel and Pease, 2021b). More specifically, when internalised bias is reinforced, it may contribute to biased and unfair targeting of socially deprived areas where poor living conditions are more concentrated (Brantingham et al., 2018; Mohler et al., 2018; Weisburd et al., 2016). Consequently, if biases in policing practices contribute to the creation of a suspect population, it can exacerbate the stigmatisation and social exclusion of specific locations (Newburn, 2011). This, in turn, may result in territorial stigmatisation, where individuals associated with these areas face additional social and territorial marginalisation (Rosten, 2017).

When conducting studies on predictive policing and resource allocation in Oslo, it can be necessary to acknowledge the notable distinctions between Oslo's east and west sides. In my study, empirical evidence reveals a concentration of violent crimes in the city centre, gradually spreading towards the eastern part of Oslo. While it is possible that crimes occurring in the central business district are influenced by routine activities and the constant influx of people throughout the day, this explanation may be different in Oslo's eastern region. The reason for crime due to routine activities may not concern Oslo's eastern region in the same way because the distribution of violent crimes in this area may also be associated with other criminogenic factors such as residential instability, low socioeconomic conditions, and ethnic heterogeneity. According to Bakken (2018), potential factors that distinguish Oslo's west and east sides are social inequalities and socioeconomic statuses. Consequently, the specific areas in the eastern part of Oslo where violent crimes are predicted may experience social disorganisation, characterised by broken homes or an early involvement in criminal behaviour (Glomseth and Aarset, 2022). Thus, understanding the differences connected to Oslo's regions may be essential for obtaining accurate and meaningful insights into the dynamics, specific needs, and possible systematic biases in the data. However, it is important to note that a higher crime prediction in Oslo's east side does not necessarily mean that Oslo's west side is safer, despite the lower number of predicted crimes.

Furthermore, stigmatisation linked to the geographical location and the cultural identity of the individuals residing in an area can manifest as territorial stigmatisation (Rosten, 2017). In her study, Rosten (2017) reveals that specific individuals in marginalised and stigmatised neighbourhoods in Oslo's eastern region may develop a "ghetto mentality" in response to the perceived prevalence of, and expectations surrounding criminal behaviour. Consequently, territorial stigmatisation and racial bias in policing can reinforce the feedback loop due to increasing apprehensions among minority populations, as the predictive algorithm consistently forecasts crimes in specific areas (Mohler et al., 2018), which can further lead to data inaccuracies or systematic errors. While the systematic bias in the data can contribute to under or over-policing, it is equally important to consider the possibility for biased interpretations from incorporating knowledge-based policing techniques. Therefore, it is critical to acknowledge the potential consequences of employing predictive policing in vulnerable areas, as subjective biases can result in unfair policing practices by targeting presumed offenders in high-risk areas (Clavell, 2018). The natural area hypothesis suggests that socially disorganised neighbourhoods are susceptible to a proliferation of criminal activities (Abbott, 1997; Weisburd et al., 2016). This proliferation aligns with territorial stigmatisation, feelings of vulnerability, and a self-fulfilling prophecy of rising crime rates. Furthermore, individuals who experience territorial stigmatisation based on their connection to socially disorganised areas may conform to culture and social norms by adopting behaviours that align with society's expectations. As a result, the interaction between police and stigmatised individuals can contribute to the feedback loop, particularly when, or if, individuals who experience arbitrary stop and search encounters are subsequently processed within the criminal justice system (Weisburd et al., 2016).

Stigmatisation as an outcome of over-policing may lead to further breakdown of trust between law enforcement and the public. This fracture in the relationship can further demote collective efficacy by triggering a cycle of breakdown, making it more challenging for the police to address and mitigate violent crimes (Braga and Clarke, 2014). Addressing this challenge can be essential because, in socially disorganised areas, informal social control can become a critical strategy for reducing violent crimes, as well as easing the widespread feeling of constant observation and social marginalisation which may reduce the overall feeling of territorial stigmatisation. Consequently, police are not welcome in these areas, and the lack of collective efficacy concerned with safety is reduced which can make residents and bystanders less likely to intervene in situations or act as capable guardians (Andresen et al., 2010). While it may be challenging to depend on social control in areas where social cohesion is low, reducing the presence of law enforcement might contribute to reduce potential stigmatisation and marginalisation, which in time might reduce the overall crime rate associated with these areas. Although the present study did not specifically examine the role of social cohesion or collective efficacy in crime prevention, future research can build upon the findings of this study to investigate the relationship between social cohesion, collective efficacy, and crime prevention. For instance, a potential avenue for future studies could involve analysing whether areas with higher levels of social cohesion and collective efficacy demonstrate lower crime rates. Additionally, future research could consider surveying registered offenders to explore if the presence of a capable guardian or strong social cohesion deterred them from engaging in criminal activities.

Furthermore, Sollund (2006) reveals that some of her ethnic minority informants in Oslo reported instances of being subjected to stop and search procedures during late-night or early-morning hours because the police found their behaviour suspicious. Therefore, it is reasonable to reflect on the role of racial bias or heightened alertness as contributing to the high number of predictions related to violent criminal behaviour in the east side. Although the present study does not contain any information concerning the offender's racial background, the data display a notable increase in violent crimes during the evening hours, specifically between 00:00 and 04:00 which might align with Sollund's (2006) discoveries. Nevertheless, the underlying motivations of stop and search practices, whether stemming from a raised suspicion due to observations, dirty policing, or a heightened state of alertness, remain unknown. In some cases, the police's subjective decisions regarding what constitutes a crime and who is deemed an offender can shape the dynamics of stop and search practices (Sandhu and Fussey, 2021). Moreover, if the predictions of high-risk areas in the east side is indeed a result of over-policing or arbitrary stop and search procedures, it could undermine the need for an enhanced collective efficacy or social cohesion within high-risk areas to establish informal social control and avoid over-policing.

Contrastingly, under-policing areas where violent crimes are less expected, whether due to predicted false negatives or internalised bias, can result in a deficiency of police presence, ultimately leading to increased crime rates and reduced public safety. Therefore, it is crucial to approach policing decisions with careful considerations in order to ensure effective allocation of resources and address potential biases tied to predictive policing. Additionally, careful considerations are necessary to ensure that the police are adequately prepared to handle violent crimes in unexpected areas.

When decisions are influenced by biased predictions, unexpected occurrences of predicted crimes may come as a surprise, as the decision-maker might not be prepared for it. Since the police cannot be present everywhere at the same time, they may miss opportunities to prevent severe crimes in areas that are not identified as high-risk. In this case, strong social cohesion and collective efficacy may be intricate for preventing violent crimes in society. Thus, crime detection can be dependent on local citizens' reports of these crimes (Mohler et al., 2018). Given the lower number of predicted crimes in Oslo's west side, potentially due to systematic errors in the data or greater residential stability fostering strong social cohesion, it is plausible that this area maintains a socially organised community with high collective efficacy, in contrast to the east side. Areas where under-policing may be a concern might need to depend on informal social control mechanisms, such as the active participation of capable bystanders, to prevent violent crimes. This active participation capable guardians can be crucial because regions affected by false negative errors might experience a lack of timely response during criminal incidents or an insufficient presence of formal social control measures.

While this section of the discussion has primarily focussed on the effects of false positive predictions, which can lead to over policing and trigger a feedback loop, it is important not to overlook the significance of false negative predictions. In their own respective ways, false negatives and false positive predictions can have critical outcomes that can significantly impact society. One area of concern is the issue of stigmatisation that arises when there is an excessive police presence in an area where it is unnecessary. Conversely, inadequate policing in areas with high crime rates can also have severe consequences, especially in cases of violent crimes. Moving forwards, it would be valuable for future research to explore the variations in predictive policing between areas with contrastive socioeconomic differences. For example, providing a more detailed examination of differences in these areas by focussing on specific crimes, or whether lower crime rates in the west are attributed to the occurrence of more severe crimes, while the east experiences a higher frequency of minor crimes. This examination could shed light on systematic differences and uncover why there are lower crime rates registered in the west. Moreover, it is essential to explore the possibility that prediction errors and biases contribute to increased targeting of marginalised or territorially stigmatised individuals. By analysing data in connection with migration patterns and socioeconomic characteristics, it may be possible to gain a better understanding of whether unique traits contribute to increased criminal activity in this part of Oslo. More specifically, it would be valuable to investigate the unique traits of these territorially stigmatised communities, such as its connection to residential instability and social structures, while also examining if there are other specific types of crimes that are more prevalent in these areas, which could impact the respective crime rates.

AI as a public "good"?

When predictive policing technology is applied accurately with no ambiguity, using the geographical perspective to comprehend crime can be important for avoiding bias or stigma connected with the offender or location. While there may be more concerns regarding predictive policing systems, data-driven policing methods can be seen as essential for governance and policymaking (Richardson et al., 2019). Therefore, using predictive policing to anticipate criminal activity may lead to an increased presence of police in a specific area, consequently lowering the probability of crimes by deterring potential offenders by increasing the associated risks of crime for the offenders (Gottfredson, Stephen and Moriarty, 2006 in Oh et al., 2021). The final discussion on whether predictive policing can be used to successfully predict crime without perpetuating increased territorial stigmatisation, is dependent on the intended use of this technology. For the police, this technology may contribute to a more effective approach to preventing and decreasing crime, as well as there can be potential biases and consequences attached to this technology. For the public, predictive policing technology may contribute to reduce crime in society and increase the feeling of safety in high-risk areas. While some issues related to over-policing, territorial stigmatisation and marginalisation still persists, and may have unintended consequences, it is likely that predictive policing technology are better than knowledge-based crime prediction. It was argued that predictive policing technology may contain some systematic errors that can contribute to under or over-policing in areas, which can be further reinforced if knowledge-based policing is applied, and the predictions may align with internalised bias. In these cases, the machine learning algorithm, provided the data is accurate, may reduce the consequences of internalised bias that comes with knowledge-based policing because it can contribute with objective data that are not subjective to bias, unless the data itself is biased due to over or under-reporting of crimes, and the feedback loop where police are repeatedly sent back to the same locations. Similarly, whom to hold responsible for prediction errors and bias will remain unknown as there may be multiple factors that can contribute to the outcome of the data prediction.

Navigating the boundaries of the present study: acknowledging limitations and embracing opportunities

As with any research endeavour, it is important to acknowledge and thoroughly discuss the limitations of the present study. Several key limitations will need to be further addressed, including those pertaining to the data itself, crime prediction techniques, and spatial analysis. Similarly, the reliability and generalisability of the crime prediction models may represent a noteworthy limitation. In this section, I will present some of the limitations encountered during this research study as well as I will present opportunities for future research of predictive policing.

Data

The data employed within this study could have been enhanced to provide better results. Specifically, the OSM data used for creating the map of Oslo exhibited certain limitations, particularly in terms of the absence of critical features such as bars, or other necessary characteristics that could have a significant impact on the predicted distribution of violent crimes in Oslo. More specifically, a significant concern with the OSM data is its potential lack of updates, leading to missing information that could have improved the accuracy and comprehensiveness of the study's findings. Consequently, it is important to acknowledge that this study may not provide perfectly accurate data, limiting its ability to make definitive contributions to existing research. Moreover, considering the MAUP, this limitation carries implications for the risk of directing police resources to areas that may suffer from either type I or type II errors due to incomplete or outdated data. In other words, there is a risk of allocating law enforcement resources disproportionately, either overlooking areas or targeting areas that may increase the feeling of surveillance and marginalisation associated with territorial policing. To address these concerns, and enhance future research, efforts should be made to improve data quality and accuracy. These efforts could involve using more up to date data sources that can provide a more detailed representation of the urban environment and possible criminogenic characteristics. Another potential improvement that could enhance data quality is implementing a focus on good routines and training in data analysis and the importance of accurate geocoding to reduce errors in the data connected to incorrect registrations of crime. For example, implementing courses or required knowledge in the training so that the officers know why they should accurately input where or when a crime happened. By researching the suggested gap for understanding predictive policing practices and increasing the focus on implementing crime predictions into the core training of police officers, it may be possible to reduce MAUP and other associated problems with predictive policing and spatial crime analysis.

Furthermore, limitations linked to the size of the data, timing and selected methods may affect the scope of the study. While a random forest model can provide accurate results, and is generally well suited for crime predictions, this analysis was limited by computational power. Thus, it would require a significant amount of time and computational resources when the dataset is large, which that may not be feasible within the scope of a master's thesis. For this reason, the chosen grid size and weekly predictions were determined based on the available resources and feasibility for this study. Furthermore, future research within the field could perform more thorough hyperparameter optimisation to enhance the model's predictability, which had to be left out of the present experiment due to computer limitations. Similarly, conducting analyses at different spatial and temporal resolutions could provide valuable insights into the underlying patterns and dynamics of crime. Therefore, future research is encouraged to explore predictive policing by measuring crime on a more detailed scale, such as neighbourhood levels or using daily predictions, and focus more on incorporating the temporal aspects of crime.

Crime prediction

The present analysis could have been more extensive, as the available data did not comprise any information on individual level. Therefore, the data could not consider any of the remaining crime dimensions as suggested by Brantingham et al. (2017). Since each element in the four dimensions could contribute to the understanding of criminogenic events, future research may address these shortcomings by integrating all four dimensions when predicting violent criminal activity, or at least more than one. Using an approach with all four crime dimensions in predictive policing could enable a more nuanced understanding of the complex interplay between the various dimensions by informing policy initiatives to prevent crime across all levels. Furthermore, data with information on a personal level may provide results contributing to understanding the individual offenders, which could be helpful in linking spatial crime with related sociodemographic or socioeconomic traits. By including personal information, it could make it possible to create an analysis focussing on where and when a crime may be more likely to happen on a more detailed level and place these results in a broader context in other cities or countries.

Furthermore, this study has been limited to predicting violent crimes with weekly trends. This study could have benefitted from incorporating a narrower focus on temporal changes in crime events. Future research that focusses more on the temporal dimension of crime could provide valuable insights into the reasons behind the occurrence of crimes in specific locations and time periods. It would be intriguing to investigate whether the increased crime rate observed from 00:00 to 04:00, for instance, can be linked to nighttime routine activities or if other factors like heightened surveillance, reduced visibility, or diminished guardianship are associated with these crimes. Additionally, incorporating a temporal focus on violent crimes might contribute to examine the connection between routine activities and areas that may be more vulnerable to criminal exposure.

At the time of this study, the Norwegian government has decided to implement receipts for stop and search procedures (Politiet, n.d). Therefore, it would be interesting to see who are frequently stopped and searched in Oslo and whether their background is connected to perceived high-risk areas. While future research may benefit from this new implementation, this study may suffer from the dark figure of crime because this study has been unable to account for, or establish a potential connection between dirty policing, bias, and increased crimes in perceived high-risk areas due to unregistered crimes. Another research suggestion for future studies would be to use algorithmic decision-making to suggest what crimes to prioritise based on their anticipated severities, mostly because the police are physically unable to address all crimes.

Smaller scale study

This study analysed violent crimes in Oslo across three distinct levels. Among these analyses, the 100x100m grid cell map emerged as the most accurate in predicting crimes at the city level. While a 100x100m grid or larger can effectively detect the violent crime distribution across Oslo, conducting studies at a smaller scale, focussing on neighbourhood levels, may uncover additional factors and trends that connect offenders and the environment. However, due to computational constraints, this analysis was unable to employ a finer grid cell size, as it would have required a significant amount of time to run the analysis. Although this study offers a general visualisation of predicted crimes in Oslo, future research could utilise these findings as a starting point to identify potential neighbourhoods for further analysis of possible criminogenic contributing factors.

Furthermore, this study has used rational choice, routine activity, and crime pattern theories as theoretical frameworks for this thesis. By focussing more on the social disorganisation theory as a framework, this could contribute to determine the fundamental relationships of people characteristics and crime, something I was unable to do for this study. Future research may investigate a community’s inability to maintain effective social control, whether due to formal or informal social control. Another significant theoretical framework for future studies for exploring the impact of physical disorder on crime, is the broken windows theory.

Generalisability

Finally, as mentioned, it is important to acknowledge that the findings of this study may not be generalisable to other research setting. Cultural, normative, and societal variation can lead to differences in criminogenic characteristics and factors contributing to crimes in various contexts. Therefore, the presence of criminogenic factors in one place does not necessarily imply their generalisability elsewhere. Additionally, each country, city, and neighbourhood have their own unique characteristics, and what may be essential in one context may not hold the same significance elsewhere. For example, weather patterns can be influential in some countries, but this factor has yet to be found significant in Norway. These differences could stem from disparities in culture or other underlying factors. Furthermore, considering that many cities share similar components such as street networks and travel paths, it would be interesting to explore how the result of this study applies to other cities with increased population.

Conclusion

The current thesis has explored the implementation of predictive policing technology within a spatial and temporal dimension. Revealing both its potential advantages and inherent limitations contributing to navigating the complexities and challenges involved in this study. The primary objective of this research was to assert to what extent the integration of machine learning technology can be used for crime prediction.

Consequently, the research questions guiding the present study were:

1. *To what extent can the integration of environmental criminology and supervised machine learning through random forest models enhance the accuracy of crime prediction?*
2. *What are the critical considerations for its effective implementation in the context of predictive policing?*

By integrating environmental criminology and supervised machine learning through random forest models, the empirical evidence in my study suggest that a combined approach could predict occurrences of violent crimes in Oslo with an accuracy of up to 80 per cent. This accuracy can be an improvement to traditional knowledge-based policing, demonstrating the efficacy of random forest models over chance-based crime prediction. In addition to its high prediction accuracy, the random forest algorithm also classified significant features that potentially influences violent crimes in specific areas. Incorporating AI-based technology for predictive policing can offer technology equipped for recognising crime patterns within the data and may objectively inform policing policies and resource allocation. The model's ability to recognise patterns and trends in the data more rapidly than human intelligence may suggest that this method is more efficient and may, with appropriate training, reduce the overall workload for crime analysts.

Using predictive policing for crime mapping can foster a proactive rather than reactive policing strategy, which can contribute to effectively decrease violent crime rates in Oslo. Correspondingly, a geographical approach to understand the crime distribution can help prevent overlooking similar crimes that can, or is likely, to happen in unexpected locations, as exemplified in the case of Oslo where the west side contrasts with the east side. Additionally, risk forecasting tools can be crucial for identifying spatiotemporal dependencies and high-risk areas, enhancing policing strategies by fostering vigilance, deterring criminal activities, and preventing future offending by reducing crime opportunities. Similarly, establishing where crimes are more likely to happen can provide valuable insight for effective governance and resource allocation. This comprehensive approach to crime prevention through AI-based technology, and sometimes environmental design, aims to create safer communities. By identifying areas that require more, or less, social control, and implementing appropriate strategies such as increased police visibility, improvement in street lighting, and surveillance, it might contribute to preventing and reducing the frequency of violent criminal activity.

Furthermore, combining supervised machine learning with the theoretical frameworks in this thesis can contribute with valuable insight and a deeper understanding of the factors influencing violent crimes in specific times and locations. Firstly, the rational choice theory offers insight into offenders' motivations and identifies features that may present opportunities for violent crimes. Secondly, incorporating routine activity theory alongside rational choice theory, crime analysts may gain significant insights into the patterns of daily routines that creates opportunistic situations where offenders can feel motivated to commit crimes. Finally, the integration of crime pattern theory, which combines elements of both rational choice theory and routine activity theory, can be instrumental in comprehending the patterns and behaviours of offenders. This theory elucidates factors within an offender's activity and awareness space that can contribute to a violent crime, allowing for the identifications of central nodes and the pathways that connects them.

In the context of predictive policing, these theoretical frameworks can help recognise potential features or situations where offenders are more likely to engage in criminal activities, and can contribute to determine areas where increased, whether formal or informal, social control can be necessary. During the discussion, I highlighted a potential connection between violent crimes ad nightlife activities. The findings of this research also predicted a higher occurrence of violent crimes in Oslo's inner city, which encompasses areas such as bars and Oslo's central station that can contribute to criminal activity as a major activity node. By considering the interactions between offenders, targets and the environment, these theoretical frameworks can provide valuable insight into the spatial and temporal dynamics of criminal activities, facilitating a more comprehensive understanding of crime patterns and aiding in the development of targeted prevention strategies.

Moreover, while advocating for the effectiveness of machine learning in implementing new policing strategies, it is crucial to acknowledge the limitations associated with adopting AI-based technology for crime prediction. The random forest model used in this study, although relatively accurate, demonstrated occasions of wrongful predictions of violent crimes, in one out of five cases. This wrongful prediction highlights the critical importance of approaching the implementation of machine learning with caution and a comprehensive understanding of its potential limitations. To mitigate the risk of systematic errors that may lead to under or over-policing in areas, it is essential to ensure that police officers possess sufficient knowledge and skills to manage advanced statistical tools and understands the implications of incorrect data registration. By doing so, it is possible to improve data quality and reduce the overall likelihood of biased outcomes. Considering the possibility and consequences of incorrect predictions, it becomes imperative to exercise discretion when interpreting and contemplating predictive policing strategies. This cautiousness can be necessary to maintain transparency and fairness in police interventions without extending current biases.

While the application of learning-based algorithms can provide valuable guidance for police actions, it also carries the risk of diminishing the critical assessment of both areas and offenders. Hence, it is imperial to recognise that neutrality of the data depends on who gathers and analyses the output. Because decisions for implementing new policies or policing strategies can affect individuals, the possibility of incorrect predictions demonstrates the importance of proper training before applying statistical findings for predictive policing. Additionally, law enforcement, or other users, should be aware of the trade-off between type I and type II errors when interpreting the data because pre-existing bias might contribute to reinforce prejudiced decisions when the data's predictions are incorrect.

Placing excessive trust in the predicted outcomes can inadvertently led to unintended biases and consequences, as it eliminates objectivity in specific situations. For example, when officers anticipate crimes in high-risk areas and actively search for potential offenders, the increased police presence in these areas can inadvertently create a paradox, contributing to an escalation in crime rates because crimes are more likely to be noticed where they are expected, creating a confirmation feedback loop where police are repeatedly sent back to the same locations. Contrastingly, biases and preconceived notions further confirmed by the data output can lead to over-policing and a disproportionate focus on minority groups or individuals connected to a predicted high-risk area. Therefore, by studying crime with a geographical focus and maintaining a nuanced approach by continually questioning and evaluating the accuracy and fairness of the predictive models, it can mitigate the risk of internalised bias and unfair policing practices and policies.

The expectations for this thesis were to explore the potential for employing machine learning in predictive policing. Throughout, the implementation of GIS and random forest models exhibited a high level of accuracy in predicting violent crimes in Oslo. These models proved to be well-suited for achieving the thesis' objectives and indicated effectiveness and suitability for crime prediction. However, the findings revealed an unexpected decrease in prediction accuracy as the grid cell size increased which suggested a homogeneity within the higher grid level, posing a challenge in identifying meaningful patterns in models greater than 100x100m. This finding raises important considerations for future research, illuminating the need for exploring alternative approaches that can capture the complexity of violent crime patterns in Oslo. Future studies may contemplate utilising reduced grid cells on a citywide scale or measuring crimes on a neighbourhood level to gain a more nuanced understanding of the crime distribution. Nevertheless, it is important to avoid potential bias and issues such as territorial stigmatisation and violating privacy laws when considering reducing the grid cell size. Additionally, it could be beneficial to explore alternative models to enrich the predictability of crime patterns. For example, it may be possible to combine random forest models with regression analysis to receive insight into the spatial distribution and criminogenic factors that potentially influence violent criminal behaviour.

The argument of limitations and potential for further research in the discussion might offer valuable insights and suggestions for improving predictive policing. These limitations encompassed data accuracy, crime prediction technologies, the scale of analysis, and generalisability. Addressing these limitations can make it possible to gain a deeper understanding of crime patterns and prevention strategies. One key recommendation for future research is to integrate individual-level data and incorporate all four dimensions to attain a more holistic approach to factors that may influence crime. Moreover, another key recommendation for future research is to prioritise improvement of data quality and accuracy, as well as a focus on improving officer training to consider clear procedures and guidelines for crime analysis emphasising the importance of consistent and precise crime registration practices. By adopting good routines and ensuring accurate crime registration, it can be possible to increase reliability of the data and diminish systematic errors. Finally, researchers should remember that findings of this thesis may not be generalisable to other research settings, emphasising the need for context-specific research and tailored prevention strategies.

Furthermore, the findings of this study offer insights into the impact of environmental factors on the occurrence of violent crimes in Oslo. These insights can inform future studies and contribute to the ongoing development of predictive policing strategies by providing a deeper understanding of the frequency of violent crimes and facilitating the prediction and prevention of crime in high-risk areas. By using machine learning to identify environmental features that influence criminal behaviour, it becomes possible to identify areas with limited social control. This information can inform law enforcement and policymakers in their decision-making process regarding crime site selection and the development of targeted policies aimed at reducing crime in these specific areas. Moreover, analysing the spatial distribution of crime locations, as well as considering patterns, routine activities, and rational choices of individual offenders, enables the identification of dynamic crime patterns. Such insights can lead to effective crime reduction interventions by addressing the underlying factors that motivate and contribute to violent criminal behaviour. Additionally, this knowledge can also be valuable for urban planners in designing environments that help prevent crime by mitigating potential crowd effects and prioritising improving social cohesion and collective efficacy in a city.

Nevertheless, it is important to be aware that using machine learning as a tool for predictive policing is not the only solution and cannot change intuitional or human police work since there is a possibility that the answer is wrong or biased. Therefore, by providing awareness of type I and type II errors in the data, this thesis may contribute to increase fairness in policing and impact community and policing efforts. A clear insight into the complexities and limitations of predictive policing technology can enable researchers and practitioners to strive towards more effective crime prevention methods and may encourage practices that will ensure appropriate statistical knowledge for performing crime analysis. By highlighting the positive and negative consequences of AI-based models for predictive policing, this thesis may contribute to future police work with an interpretation for how such technology can contribute to reducing the workload in predictive policing.

In summary, with technology's rapid advancement in contemporary society, this research demonstrates the necessity of keeping law enforcement, and other stakeholders, up to date with ever-changing technology. This thesis illuminates the need for implementing strategies and practices in police training for employing predictive policing tools and accurately register crime data. By embracing data-driven technology as a compliment to human decision-making, it becomes possible to leverage objective insights that can mitigate issues such as under or over-policing and territorial stigmatisation. While the objectivity of data depends on interpretation, the integration of predictive policing with knowledge-based approaches can be essential for minimising type I and type II errors and ensure law enforcement is presence where it is most needed. This data-driven approach offers significant contributions to knowledge-based policing by surpassing random chance predictions and facilitating the rapid identification of violent crime patterns. Nonetheless, the implementation of predictive policing should be approached with caution, considering potential unintended consequences such as reinforcing biases, or failing to address crime in unexpected areas. Striking a delicate balance between effectively using predictive policing technology and fostering social cohesion becomes paramount in maintaining fair and equitable policing practices. In conclusion, despite its limitations, supervised machine learning through random forest and GIS proves valuable as a supplementary tool in decision-making for law enforcement agencies. By acknowledging its flaws, and implementing this technology sensibly, predictive policing has the potential to enhance the efficiency and effectiveness of policing practices, contributing to safer communities.

Table of Reference

Abbott A (1997) Of Time and Space: The Contemporary Relevance of the Chicago School. *Social Forces* 75(4): 1149-1182. DOI: 10.1093/sf/75.4.1149

Abrams DS (2021) Covid and Crime: An Early Empirical Look. *Journal of Public Economics* 194. DOI: https://doi.org/10.1016/j.jpubeco.2020.104344

Almanie T, Mirza R and Lor E (2015) Crime Prediction Based on Crime Types and Using Spatial and Temporal Criminal Hotspots. *International Journal of Data Mining* 5(4): 1-19. DOI: 10.5121/ijdkp.2015.5401

Alpaydin E (2014) *Introduction to Machine Learning.* Cambridge, MA: The MIT Press.

Alves LGA, Ribeiro HV and Rodrigues FA (2018) Crime Prediction through Urban Metrics and Statistical Learning. *Physica A: Statistical Mechanics and its Applications* 505: 435-443. DOI: https://doi.org/10.1016/j.physa.2018.03.084

Andersen B, Gerell M and Hanssen GS (2021) Nou 2020:16: Levekår I Byer. Gode Lokalsamfunn for Alle. *Nordic Journal of Urban Studies.* Universitetsforlaget, 78-90.

Andresen MA (2008) Gis and Spatial Analysis. In: Bruninsma GJN and Johnson SD (eds) *The Oxford Handbook of Enviornmental Criminology*. New York: Oxford University Press:190-210.

Andresen MA (2010) The Place of Environmental Criminology within Criminological Thought. In: Andresen MA, Brantingham PJ and Kinney JB (eds) *Classics in Environmental Criminology*. Burnaby: Simon Fraser University Publications: 6-28.

Andresen MA (2020) *Enviornmental Criminology: Evolution, Theory and Practice.* New York, NY: Routledge.

Andresen MA, Brantingham PJ and Kinney JB (2010) *Classics in Environmental Criminology.* Burnaby: Simon Fraser University Publications.

Andresen MA and Malleson N (2011) Testing the Stability of Crime Patterns: Implications for Theory and Policy. *Journal of Research in Crime and Delinquency* 48(1): 58-82. DOI: 10.1177/0022427810384136

Anselin L, Cohen J, Cook D, et al. (2000) Spatial Analyses of Crime. *Criminal justice* 4(2): 213-262.

Araújo A, Cacho N, Bezerra L, et al. (2018) Towards a Crime Hotspot Detection Framework for Patrol Planning. *2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS).* 1256-1263.

Babakura A, Sulaiman MN and Yusuf MA (2014) Improved Method of Classification Algorithms for Crime Prediction. *2014 International Symposium on Biometrics and Security Technologies (ISBAST).* Kuala Lumpur, Malaysia, 250-255.

Babuta A and Oswald M (2021) Machine Learning Predictive Algorithms and the Policing of Future Crimes: Governance and Oversight. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge:214-236.

Bakken A (2018) *Ung I Oslo 2018.* Oslo Metropolitan University-OsloMet: NOVA.

Berk R (2010) An Introduction to Statistical Learning from a Regression Perspective. In: Piquero AR and Weisburd D (eds) *Handbook of Quantitative Criminology*. New York, NY: Springer: 725-740.

Berk R (2013) Algorithmic Criminology. *Security Informatics* 2(1): 1-14. DOI: 10.1186/2190-8532-2-5

Berk RA and Bleich J (2013) Statistical Procedures for Forecasting Criminal Behavior: A Comparative Assessment Forecasting Criminal Behavior: Research Article.

Criminology & Public Policy 12: 513-544. DOI: https://heinonline.org/HOL/P?h=hein.journals/crpp12&i=529
Bernasco W and Steenbeek W (2017) More Places Than Crimes: Implications for Evaluating the Law of Crime Concentration at Place. *Journal of Quantitative Criminology* 33(3): 451-467. DOI: 10.1007/s10940-016-9324-7
Bjørgo T and Myhrer TG (2015) *Forskningsetisk Veileder for Politihøgskolen.* Oslo: Politihøgskolen.
Block RL and Block CR (1995) Space, Place and Crime: Hot Spot Areas and Hot Places of Liquor-Related Crime. *Crime and place* 4(2): 145-184.
Boudon R (1998) Limitations of Rational Choice Theory. *American Journal of Sociology* 104(3): 817-828. DOI: 10.1086/210087
Bowers KJ, Johnson SD and Pease K (2004) Prospective Hot-Spotting: The Future of Crime Mapping? *The British Journal of Criminology* 44(5): 641-658. DOI: 10.1093/bjc/azh036
Braga AA and Clarke RV (2014) Explaining High-Risk Concentrations of Crime in the City: Social Disorganization, Crime Opportunities, and Important Next Steps. *Journal of Research in Crime and Delinquency* 51(4): 480-498.
Brantingham PJ and Brantingham PL (1991) *Enivronmental Criminology.* Illinois: Waveland Inc.
Brantingham PJ and Brantingham PL (2008) Crime Pattern Theory. In: Wortley R and Mazerolle L (eds) *Environmental Criminology and Crime Analysis*. London: Willan:78-94.
Brantingham PJ, Brantingham PL and Andresen MA (2017) The Geometry of Crime and Crime Pattern Theory. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*. Second ed. New York, NY: Routledge:98-115.
Brantingham PJ, Valasik M and Mohler GO (2018) Does Predictive Policing Lead to Biased Arrests? Results from a Randomized Controlled Trial. *Statistics and Public Policy* 5(1): 1-6. DOI: 10.1080/2330443X.2018.1438940
Brantingham PL and Brantingham PJ (1993a) Environment, Routine and Situation: Toward a Pattern Theory of Crime. *Advances in Criminological Theory* 5: 259–294.
Brantingham PL and Brantingham PJ (1993b) Nodes, Paths and Edges: Considerations on the Complexity of Crime and the Physical Environment. *Journal of Environmental Psychology* 13(1): 3-28. DOI: https://doi.org/10.1016/S0272-4944(05)80212-9
Breiman L (2001) Random Forests. *Machine Learning* 45(1): 5-32. DOI: 10.1023/A:1010933404324
Brownstein HH (1999) *The Social Reality of Violence and Violent Crime.* Needham Heights, MA: Allyn and Bacon.
Bruinsma G, Yang S-M, Gill C, et al. (2016) The Importance of Place in Mainstream Criminology and Related Fields: Influences and Lessons to Be Learned. In: Weisburd D, Eck JE, Braga AA, et al. (eds) *Place Matters: Criminology for the Twenty-First Century*. New York, NY: Cambridge University Press:68-85.
Bruinsma GJN and Johnson SD (2018) Environmental Criminology: Scope, History, and State of the Art. In: Bruinsma GJN and Johnson SD (eds) *The Oxford Handbook of Environmental Criminology*. Oxford University Press:1-32.
Burgess EW (1916) Juvenile Delinquency in a Small City. *Journal of the American Institute of Criminal Law and Criminology* 6: 724-728.
Caplan JM, Kennedy LW and Piza EL (2013) Joint Utility of Event-Dependent and Environmental Crime Analysis Techniques for Violent Crime Forecasting. *Crime & Delinquency* 59(2): 243-270. DOI: 10.1177/0011128712461901

Carroll J and Weaver F (1986) Shoplifters' Perceptions of Crime Opportunities: A Process-Tracing Study. In: Cornish DB and Clarke RV (eds) *The Reasoning Criminal: Rational Choice Perspectives on Offending*. New York, NY: Springer-Verlag:19-38.
Castelvecchi D (2016) Can We Open the Black Box of Ai? *Nature* 538(7623): 20–23. DOI: 10.1038/538020a
Chan J (2021) The Future of Ai in Policing: Exploring the Sociotechnical Imaginaries. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge:41-57.
Clavell GG (2018) Exploring the Ethical, Organisational and Technological Challenges of Crime Mapping: A Critical Approach to Urban Safety Technologies. *Ethics and Information Technology* 20(4): 265-277. DOI: 10.1007/s10676-018-9477-1
Cohen G and Graver H (2021) What Big Data in Health Care Can Teach Us About Predictive Policing. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge:111-131.
Cohen LE and Felson M (1979) Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review* 44(4): 588-608. DOI: 10.2307/2094589
Collins ME and Loughran TA (2017) Rational Choice Theory, Heuristics, and Biases. In: Bernasco W, van Gelder J-L and Elffers H (eds) *The Oxford Handbook of Offender Decision Making*. Oxford University Press:10-23.
Committees TNNRE (2019) *Guidelines for Research Ethics in the Social Sciences, Humanities, Law and Theology*. Available at: https://www.forskningsetikk.no/en/guidelines/social-sciences-humanities-law-and-theology/guidelines-for-research-ethics-in-the-social-sciences-humanities-law-and-theology/ (accessed 16th May).
Cornish DB and Clarke RV (1986) *The Reasoning Criminal: Rational Choice Perspectives on Offending.* New York, NY: Springer-Verlag.
Cornish DB and Clarke RV (2017) The Rational Choice Perspective. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*. Second ed. New York, NY: Routledge:29-61.
Cornish DB and Clarke RVG (1987) Understanding Crime Displacement: An Application of Rational Choice Theory. *Criminology* 25: 933–947.
Day P, Breetzke G, Kingham S, et al. (2012) Close Proximity to Alcohol Outlets Is Associated with Increased Serious Violent Crime in New Zealand. *Australian and New Zealand Journal of Public Health* 36(1): 48-54. DOI: https://doi.org/10.1111/j.1753-6405.2012.00827.x
Deryol R, Wilcox P, Logan M, et al. (2016) Crime Places in Context: An Illustration of the Multilevel Nature of Hot Spot Development. *Journal of Quantitative Criminology* 32(2): 305-328. DOI: https://doi.org/10.1007/s10940-015-9278-1
Drummond C and Holte RC (2003) C4. 5, Class Imbalance, and Cost Sensitivity: Why under-Sampling Beats over-Sampling. *Workshop on learning from imbalanced datasets II.* 1-8.
Eck J (2003) Police Problems: The Complexity of Problem Theory, Research and Evaluation. *Crime prevention studies* 15: 79-114.
Eck J and Weisburd DL (2015) Crime Places in Crime Theory *Crime and Place: Crime Prevention Studies* 4: 1-33.
Feeney F (1986) Robbers as Decision-Makers. In: Cornish DB and Clarke RV (eds) *The Reasoning Criminal: Rational Choice Perspectives on Offending*. New York, NY: Springer-Verlag: 53-71.
Felson M (1986) Linking Criminal Choices, Routine Activities, Informal Control, and Criminal Outcomes. In: Cornish DB and Clarke RV (eds) *The Reasoning Criminal:*

Rational Choice Perspectives on Offending. New York, NY: Springer-Verlag: 119-155.
Felson M (1987) Routine Activities and Crime Prevention in the Developing Metropolis. *Criminology* 25(4): 911–931. DOI: https://onlinelibrary.wiley.com/doi/10.1111/j.1745-9125.1987.tb00825.x
Felson M (2010) What Every Mathematician Should Know About Modelling Crime. *European Journal of Applied Mathematics* 21(4-5): 275-281. DOI: https://doi.org/10.1017/S0956792510000070
Felson M (2017) The Routine Activity Approach. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*. Second ed. New York, NY: Routledge: 29-61.
Felson M and Boba R (2010) *Crime and Everyday Life.* California: Sage.
Felson M and Clarke RV (1998) Opportunity Makes the Thief: Practical Theory for Crime Prevention. *Police Research Series Paper* 98: 4-8.
Ferguson AG (2017) Policing Predictive Policing. *Washington University Law Review* 94(5): 1109-1190.
Gerell M (2021) Does the Association between Flows of People and Crime Differ across Crime Types in Sweden? *European Journal on Criminal Policy and Research* 27(3): 433-449. DOI: 10.1007/s10610-021-09478-3
Gerell M, Allvin A, Frith M, et al. (2022) Covid-19 Restrictions, Pub Closures, and Crime in Oslo, Norway. *Nordic Journal of Criminology*: 1-20. DOI: 10.1080/2578983X.2022.2100966.
Glomseth R and Aarset MV (2022) Violent Crime among Children and Juveniles in Oslo in 2020: Policing Challenges, Responses, and Experiences. In: Albrecht JF and den Heyer G (eds) *Understanding and Preventing Community Violence: Global Criminological and Sociological Perspectives*. Cham: Springer: 23-45.
Goldthorpe JH (1998) Rational Action Theory for Sociology. *The British Journal of Sociology* 49(2): 167-192. DOI: 10.2307/591308
Gorr W and Harries R (2003) Introduction to Crime Forecasting. *International Journal of Forecasting* 19(4): 551-555. DOI: https://doi.org/10.1016/S0169-2070(03)00089-X
Gorr WL and Lee Y (2015) Early Warning System for Temporary Crime Hot Spots. *Journal of Quantitative Criminology* 31(1): 25-47. DOI: 10.1007/s10940-014-9223-8
Groff ER and Lockwood B (2014) Criminogenic Facilities and Crime across Street Segments in Philadelphia: Uncovering Evidence About the Spatial Extent of Facility Influence. *Journal of Research in Crime and Delinquency* 51(3): 277-314.
Guerry AM (1833) *Essai Sur La Statistique Morale De La France.* Paris: Crochard.
Gundhus HI (2012) Experience or Knowledge? Perspectives on New Knowledge Regimes and Control of Police Professionalism. *Policing: A Journal of Policy and Practice* 7(2): 178-194. DOI: 10.1093/police/pas039
Hamilton M (2021) Predictive Policing through Risk Assessment. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge: 58-78.
Hapfelmeier A and Ulm K (2013) A New Variable Selection Approach Using Random Forests. *Computational Statistics & Data Analysis* 60: 50-69. DOI: https://doi.org/10.1016/j.csda.2012.09.020
Hardyns W and Rummens A (2018) Predictive Policing as a New Tool for Law Enforcement? Recent Developments and Challenges. *European Journal on Criminal Policy and Research* 24(3): 201-218. DOI: 10.1007/s10610-017-9361-2
Harries KD (1974) Intraurban Crime Patterns. In: Andresen MA, Brantingham PJ and Kinney JB (eds) *Classics in Environmental Criminology*. Burnaby: Simon Fraser University Publications:155-180.

Hart R, Pedersen W and Skardhamar T (2019) Blowing in the Wind? The Effect of Weather on the Intensity and Spatial Distribution of Crime. Report.

Haygen H and Skilbrei M-L (2021) *Håndbok I Forskningsetikk Og Databehandling.* Oslo: Fagbokforlaget.

Hechter M and Kanazawa S (1997) Sociological Rational Choice Theory. *Annual Review of Sociology* 23: 191-214. DOI: https://doi.org/10.1146/annurev.soc.23.1.191

Hipp JR and Williams SA (2020) Advances in Spatial Criminology: The Spatial Scale of Crime. *Annual Review of Criminology* 3(1): 75-95. DOI: 10.1146/annurev-criminol-011419-041423

Hoppe L and Gerell M (2019) Near-Repeat Burglary Patterns in Malmö: Stability and Change over Time. *European Journal of Criminology* 16(1): 3-17.

Ignatans D and Pease K (2008) Crime Concentrations: Hot Dots, Hotspots and Hot Flushes. In: Bruninsma GJN and Johnson SD (eds) *The Oxford Handbook of Enviornmental Criminology*. New York: Oxford University Press:664-691.

Jacobsen J and Sandvik VH (2015) An Outline of the New Norwegian Criminal Code. *Bergen Journal of Criminal Law and Criminal Justice* 3(2): 162-183.

James G, Witten D, Hastie T, et al. (2013) *An Introduction to Statistical Learning: With Applications in R.* New York, NY: Springer.

Jeffery CR (1969) Crime Prevention and Control through Environmental Engineering. *Criminologica* 7: 35–58.

Jeffery CR (1976) Criminal Behavior and the Physical Environment: A Perspective. *American Behavioral Scientist* 20: 149-174.

Johnson SD (2017) Crime Mapping and Spatial Analysis. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*. Second ed. New York, NY: Routledge:199-223.

Jones S (2000) *Understanding Violent Crime.* Buckingham: Open University Press.

Jordan MI and Mitchell TM (2015) Machine Learning: Trends, Perspectives, and Prospects. *Science* 349(6245): 255-260. DOI: doi:10.1126/science.aaa8415

Jung J, Patnam M and Ther-Martirosyan A (1993) An Algorithmic Crystal Ball: Forecasts-Based on Machine Learning. *IMF Working Papers* 18(1).

Kaufmann M, Egbert S and Leese M (2019) Predictive Policing and the Politics of Patterns. *The British Journal of Criminology* 59(3): 674-692. DOI: https://doi.org/10.1093/bjc/azy060

Kirk DS (2009) A Natural Experiment on Residential Change and Recidivism: Lessons from Hurricane Katrina. *American Sociological Review* 74(3): 484-505.

Kondo MC, Andreyeva E, South EC, et al. (2018) Neighborhood Interventions to Reduce Violence. *Annual Review of Public Health* 39(1): 253-271. DOI: 10.1146/annurev-publhealth-040617-014600

Kooistra EB (2021) Substance Abuse, Self-Control and Crime. In: van Rooij B and Sokol DD (eds) *The Cambridge Handbook of Compliance*. Cambridge: Cambridge University Press:499-515.

Kounadi O, Ristea A, Araujo A, et al. (2020) A Systematic Review on Spatial Crime Forecasting. *Crime Science* 9(1): 1-22. DOI: 10.1186/s40163-020-00116-7

Kubrin CE and Weitzer R (2003) New Directions in Social Disorganization Theory. *Journal of Research in Crime and Delinquency* 40(4): 374-402. DOI: 10.1177/0022427803256238

Kuhn M and Johnson K (2019) *Feature Engineering and Selection: A Practical Approach for Predictive Models.* Boca Raton, FL: CRC Press.

Lanestedt G (2016) Stordata Og Kunnskapsbasert Forvaltning. *Stat & Styring* 26(2): 52-54. DOI: 10.18261/ISSN0809-750X-2016-02-18

Larsson P, Eriksen T, Pedersen C, et al. (2022) Langsiktige Trender I Kriminalitetsbildet: Vurderinger Av Metoder for Beskrivelse Av Fremtidig Kriminalitetsutvikling. Report: Justis- og beredskapsdepartementet.

Lin Y-L, Yen M-F and Yu L-C (2018) Grid-Based Crime Prediction Using Geographical Features. *ISPRS International Journal of Geo-Information* 7(8): 298. DOI: https://doi.org/10.3390/ijgi7080298

Lovelace R, Nowosad J and Muenchow J (2019) *Geocomputation with R.* Boca Raton, FL: CRC Press.

Malleson N and Andresen MA (2016) Exploring the Impact of Ambient Population Measures on London Crime Hotspots. *Journal of Criminal Justice* 46: 52-63. DOI: https://doi.org/10.1016/j.jcrimjus.2016.03.002

Matsueda RL, Kreager DA and Huizinga D (2006) Deterring Delinquents: A Rational Choice Model of Theft and Violence. *American Sociological Review* 71(1): 95-122. DOI: 10.1177/000312240607100105

McDaniel JLM and Pease K (2021a) Conclusion. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge:289-297.

McDaniel JLM and Pease K (2021b) Introduction. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge:1-38.

Mills CW (2000[1959]) The Sociological Imagination. New York: Oxford University Press.

Miró F (2014) Routine Activity Theory. *The Encyclopedia of Theoretical Criminology*: 1-7. DOI: https://onlinelibrary.wiley.com/doi/full/10.1002/9781118517390.wbetc198

Mohler G and Porter MD (2018) Rotational Grid, Pai-Maximizing Crime Forecasts. *Statistical Analysis and Data Mining: The ASA Data Science Journal* 11(5): 227-236. DOI: https://doi.org/10.1002/sam.11389

Mohler G, Raje R, Carter J, et al. (2018) A Penalized Likelihood Method for Balancing Accuracy and Fairness in Predictive Policing. *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC).* 2454-2459.

Morris T and Mannheim H (1957) *The Criminal Area: A Study in Social Ecology.* Oxon: Routledge.

Murray AT, McGuffog I, Western JS, et al. (2001) Exploratory Spatial Data Analysis Techniques for Examining Urban Crime: Implications for Evaluating Treatment. *The British Journal of Criminology* 41(2): 309-329. DOI: 10.1093/bjc/41.2.309

Nagin DS (2010) Group-Based Trajectory Modeling: An Overview. In: Piquero AR and Weisburd D (eds) *Handbook of Quantitative Criminology*. New York, NY: Springer: 53-68.

Newburn T (2011) Policing Youth Anti-Social Behaviour and Crime: Time for Reform. *Journal of children's services* 6(2): 96-105. DOI: https://doi.org/10.1108/17466661111149394

Newton A and Felson M (2015) Editorial: Crime Patterns in Time and Space: The Dynamics of Crime Opportunities in Urban Areas. *Crime Science* 4(1): 11. DOI: 10.1186/s40163-015-0025-6

Nguyen TT, Hatua A and Sung AH (2017) Building a Learning Machine Classifier with Inadequate Data for Crime Prediction. *Journal of Advances in Information Technology* 8(2): 141-147.

Oh G, Song J, Park H, et al. (2021) Evaluation of Random Forest in Crime Prediction: Comparing Three-Layered Random Forest and Logistic Regression. *Deviant Behavior*: 1-14. DOI: 10.1080/01639625.2021.1953360

Pearsall B (2010) Predictive Policing: The Future of Law Enforcement. *National Institute of Justice Journal* 266(1): 16-19.

Piquero AR and Weisburd D (2010) *Handbook of Quantitative Criminology.* New York, NY: Springer.
Politiet (n.d) *Notification of a Trial Receipt Scheme*. Available at: https://www.politiet.no/globalassets/dokumenter/oslo/kvitteringsordning/kvitteringsordning---english.pdf (accessed 14th May).
Politiet (n.d.) *Anmeldt Kriminalitet*. Available at: https://www.politiet.no/aktuelt-tall-og-fakta/tall-og-fakta/anmeldt-kriminalitet-strasak/ (accessed 16th May).
Qiang W and Zhongli Z (2011) Reinforcement Learning Model, Algorithms and Its Application. *2011 International Conference on Mechatronic Science, Electric Engineering and Computer (MEC).* 1143-1146.
Quetelet LAJ (1842) Of the Development of the Propensity to Crime. *A Treatise on Man and the Development of His Faculties*. Edinburgh: W. and R. Chambers: 82–96.
Ranson M (2014) Crime, Weather, and Climate Change. *Journal of Environmental Economics and Management* 67(3): 274-302. DOI: https://doi.org/10.1016/j.jeem.2013.11.008
Ratcliffe J (2004) Geocoding Crime and a First Estimate of an Acceptable Minimum Hit Rate. *International Journal of Geographical Information Science* 18: 61-72. DOI: 10.1080/13658810310001596076
Ratcliffe J (2010) Crime Mapping: Spatial and Temporal Challenges. In: Piquero AR and Weisburd D (eds) *Handbook of Quantitative Criminology*. New York, NY: Springer: 5-24.
Ratcliffe JH (2006) A Temporal Constraint Theory to Explain Opportunity-Based Spatial Offending Patterns. *Journal of Research in Crime and Delinquency* 43(3): 261-291. DOI: 10.1177/0022427806286566
Ratcliffe JH (2012) The Spatial Extent of Criminogenic Places: A Changepoint Regression of Violence around Bars. *Geographical Analysis* 44(4): 302-320. DOI: https://doi.org/10.1111/j.1538-4632.2012.00856.x
Richardson R, Schultz JM and Crawford K (2019) Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice. *New York Law Review Online* 94(15): 15-55. DOI: https://heinonline.org/HOL/P?h=hein.journals/nyulro94&i=14
Rinnan Å, Berg Fvd and Engelsen SB (2009) Review of the Most Common Pre-Processing Techniques for near-Infrared Spectra. *Trends in Analytical Chemistry* 28(10): 1201-1222. DOI: https://doi.org/10.1016/j.trac.2009.07.007
Roncek DW and Bell R (1981) Bars, Blocks, and Crimes. *Journal of environmental systems* 11(1): 35-47.
Rossow I and Norström T (2012) The Impact of Small Changes in Bar Closing Hours on Violence. The Norwegian Experience from 18 Cities. *Addiction* 107(3): 530-537. DOI: https://doi.org/10.1111/j.1360-0443.2011.03643.x
Rosten MG (2017) Territoriell Stigmatisering Og Gutter Som «Leker Getto» I Groruddalen. *Norsk sosiologisk tidsskrift* 1(1): 53-70. DOI: 10.18261/issn.2535-2512-2017-01-04
Saeed U, Sarim M, Usmani A, et al. (2015) Application of Machine Learning Algorithms in Crime Classification and Classification Rule Mining. *Research Journal of Applied Sciences* 4(3): 106-114. DOI: 15.ISCA-RJRS-2013-1005
Sampson RJ and Groves WB (1989) Community Structure and Crime: Testing Social-Disorganization Theory. *American Journal of Sociology* 94(4): 774-802. DOI: 10.1086/229068
Sandhu A and Fussey P (2021) The 'Uberization of Policing'? How Police Negotiate and Operationalise Predictive Policing Technology. *Policing and Society* 31(1): 66-81. DOI: 10.1080/10439463.2020.1803315

Santos RB (2017) *Crime Analysis with Crime Mapping.* California: Sage Publications.
Satz D and Ferejohn J (1994) Rational Choice and Social Theory. *The Journal of Philosophy* 91(2): 71-87. DOI: 10.2307/2940928
Selten F, Robeer M and Grimmelikhuijsen S (2023) 'Just Like I Thought': Street-Level Bureaucrats Trust Ai Recommendations If They Confirm Their Professional Judgment. *Public Administration Review* 83(2): 263-278. DOI: https://doi.org/10.1111/puar.13602
Shapiro A (2021) Accountability and Indeterminacy in Predictive Policing. In: McDaniel JLM and Pease K (eds) *Predictive Policing and Artificial Intelligence*. Oxon: Routledge:185-213.
Shaw CR and McKay HD (1969) Juvenile Delinquency and Urban Areas: A Study of Rates of Delinquency in Relation to Differential Characteristics of Local Communities in American Cities. In: Andresen MA, Brantingham PJ and Kinney JB (eds) *Classics in Environmental Criminology*. Canada: Simon Fraser University Publications:87-119.
Sherman LW, Gartin PR and Buerger ME (1989) Hot Spots of Predatory Crime: Routine Activities and the Criminology of Place. *Criminology* 27(1): 27-55. DOI: https://doi.org/10.1111/j.1745-9125.1989.tb00862.x
Sidebottom A and Tilley N (2017) Situational Crime Prevention and Offender Decision Making. In: Bernasco W, van Gelder J-L and Elffers H (eds) *The Oxford Handbook of Offender Decision Making*. New York, NY: Oxford University Press:67–86.
Solhjell R (2019) «Hele Skolen Trenger Ikke Den Oppmerksomheten». *Nordisk politiforskning* 6(2): 156-168. DOI: 10.18261/issn.1894-8693-2019-02-06
Sollund R (2006) Racialisation in Police Stop and Search Practice – the Norwegian Case. *Critical Criminology* 14(3): 265-292. DOI: 10.1007/s10612-006-9012-2
SSB (2022a) *Fakta Om Landskap I Norge*. Available at: https://www.ssb.no/natur-og-miljo/faktaside/landskap-i-norge (accessed 18th November).
SSB (2022b) *Kommune Oslo (Oslo)*. Available at: https://www.ssb.no/kommunefakta/oslo (accessed 18th November).
Stene RJ (2017) *Classification of Type of Offence*. Available at: https://www.ssb.no/en/klass/klassifikasjoner/146/koder (accessed 1st November).
Suthaharan S (2015) Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning. London: Springer.
Teknologirådet (2016) Teknologirådets Beretning for 2015. Report, 31.03.2016.
Tennøy A, Øksenholt K and Aarhaug J (2014) Transport Effects and Environmental Consequences of Central Workplace Location. *Transportation Research Procedia* 4: 14-24. DOI: 10.1016/j.trpro.2014.11.002
Thomas SA and Drawve G (2018) Examining Interactive Effects of Characteristics of the Social and Physical Environment on Aggravated Assault. *Journal of Criminal Justice* 57: 89-98. DOI: https://doi.org/10.1016/j.jcrimjus.2018.04.002
Tillyer MS and Eck JE (2011) Getting a Handle on Crime: A Further Extension of Routine Activities Theory. *Security Journal* 24(2): 179-193. DOI: https://doi.org/10.1057/sj.2010.2
Townsley M (2017) Offender Mobility. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*. Second ed. New York, NY: Routledge:142-161.
UiO (n.d.) *Services for Sensitive Data (Tsd)*. Available at: https://www.uio.no/english/services/it/research/sensitive-data/index.html (accessed 16th May).
Uittenbogaard A and Ceccato V (2014) Safety in Stockholm's Underground Stations: An Agenda for Action. *European Journal on Criminal Policy and Research* 20(1): 73-100. DOI: 10.1007/s10610-013-9212-8

Vieira SM, Kaymak U and Sousa JMC (2010) Cohen's Kappa Coefficient as a Performance Measure for Feature Selection. *International Conference on Fuzzy Systems.* Barcelona, Spain, 1-8.

Wacquant L, Slater T and Pereira VB (2014) Territorial Stigmatization in Action. *Environment and Planning A: Economy and Space* 46(6): 1270-1280. DOI: 10.1068/a4606ge

Wang B, Yin P, Bertozzi AL, et al. (2019) Deep Learning for Real-Time Crime Forecasting and Its Ternarization. *Chinese Annals of Mathematics, Series B* 40(6): 949-966. DOI: 10.1007/s11401-019-0168-y

Weisburd D (2015) The Law of Crime Concentration and the Criminology of Place. *Criminology* 53(2): 133-157. DOI: https://doi.org/10.1111/1745-9125.12070

Weisburd D, Eck JE, Braga AA, et al. (2016) *Place Matters: Criminology for the Twenty-First Century.* New York, NY: Cambridge University Press.

Wessel T, Turner LM and Nordvik V (2018) Population Dynamics and Ethnic Geographies in Oslo: The Impact of Migration and Natural Demographic Change on Ethnic Composition and Segregation. *Journal of Housing and the Built Environment* 33(4): 789-805. DOI: 10.1007/s10901-017-9589-7

Wheeler AP and Steenbeek W (2021) Mapping the Risk Terrain for Crime Using Machine Learning. *Journal of Quantitative Criminology* 37(2): 445-480. DOI: 10.1007/s10940-020-09457-7

Wortley R and Townsley M (2017) Environmental Criminology and Crime Analysis: Environmental Criminology and Crime Analysis: Situating the Theory, Analytic Approach and Application. In: Wortley R and Townsley M (eds) *Environmental Criminology and Crime Analysis*. Second ed. New York, NY: Routledge: 1-26.

Xia Z, Stewart K and Fan J (2021) Incorporating Space and Time into Random Forest Models for Analyzing Geospatial Patterns of Drug-Related Crime Incidents in a Major U.S. Metropolitan Area. *Computers, Environment and Urban Systems* 87: 1-16. DOI: 10.1016/j.compenvurbsys.2021.101599

Ye H, Brown M and Harding J (2014) Gis for All: Exploring the Barriers and Opportunities for Underexploited Gis Applications. *OSGEO Journal* 13: 19-28.

Zhang X, Liu L, Xiao L, et al. (2020) Comparison of Machine Learning Algorithms for Predicting Crime Hotspots. *IEEE Access* 8: 181302-181310. DOI: 10.1109/ACCESS.2020.3028420

Appendix

Appendix 1: Data variables

STRASAK	OSM	MET
Address	Buildings	Average temperature
Adjacent cells 1-8	Land use	Sum millimetres of rain
Crime type	Roads and paths	Year and week
Crime group	Minor roads	
Date from	Natural beach	
Time lag	Place of worship	
Week	Names of places	
X	Places of recreation	
Y	Railways	
Year	Traffic	
Year and week	transport stations	

Table 10: Data variables

Variable explanation

Address – Address where crimes are registered

Adjacent – Adjacent grid cells

Crime group – Specific types of violent crime

Crime type – Violent crimes

Date from – Date of registration

Time lag – Weekly spatial time lag

Week – Week of crime registration

X – Coordinate X

Y – Coordinate Y

Year – Year of crime

Year and week - Year and week variable

Buildings – Building outlines

Major roads – Motorway, important roads, ...

Land use – Forest, residential areas, ...

Roads and paths – Roads, tracks, ...

Natural beach – natural area, wetlands, ...

Place of worship – Churches, mosques, ...

Names of places – Cities, towns, ...

Places of interest – Public facilities, ...

Railways – Railway, subway, ...

Transport stations – Parking, petrol station, ...

Traffic – Traffic lights, crossing, ...

Average temperature

Sum millimetres of rain

Appendix 2: Random forest variable importance plot

100x100m variable importance plot

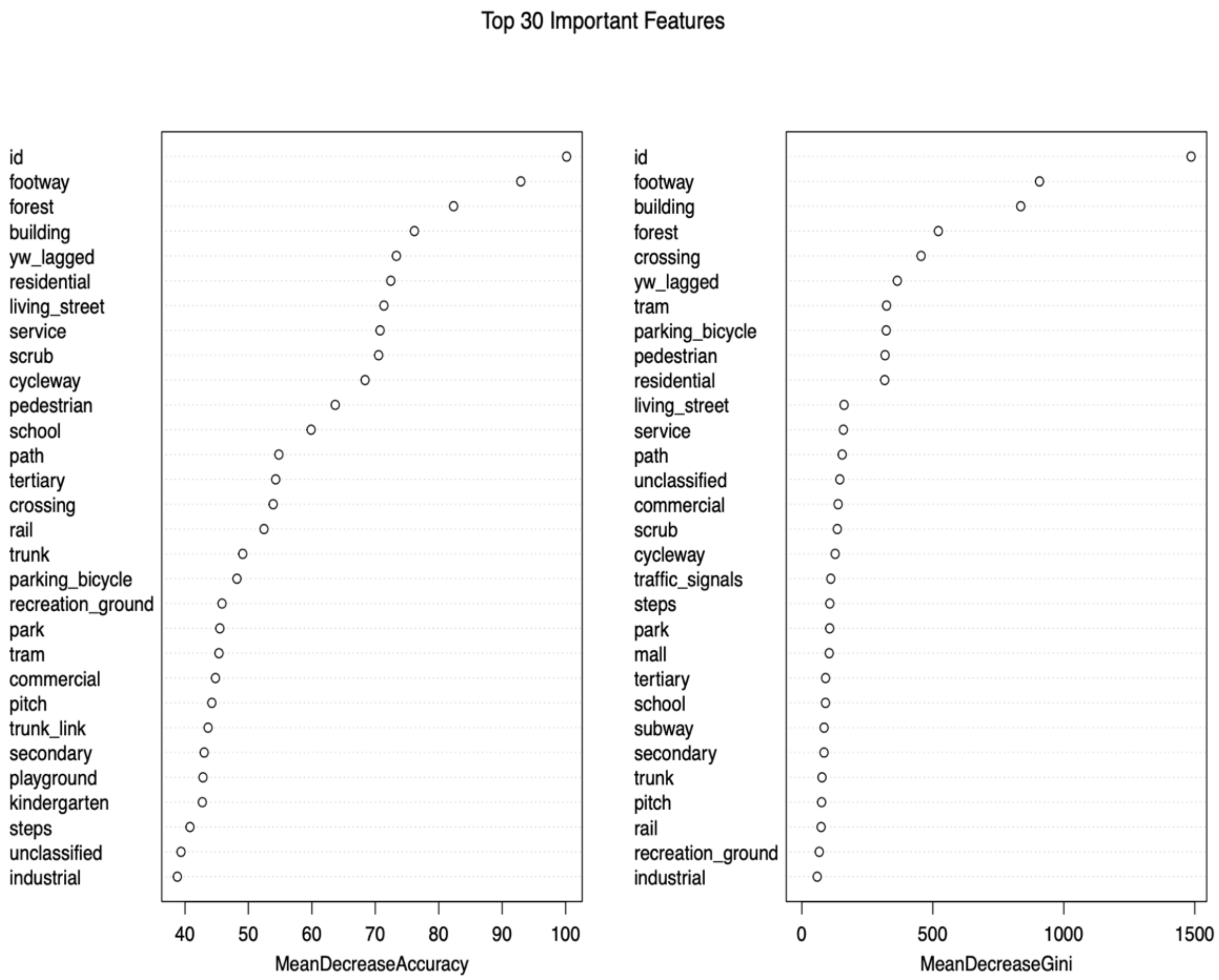

Figure 7: Random forests – 100x100m variable importance plot

250x250m variable importance plot

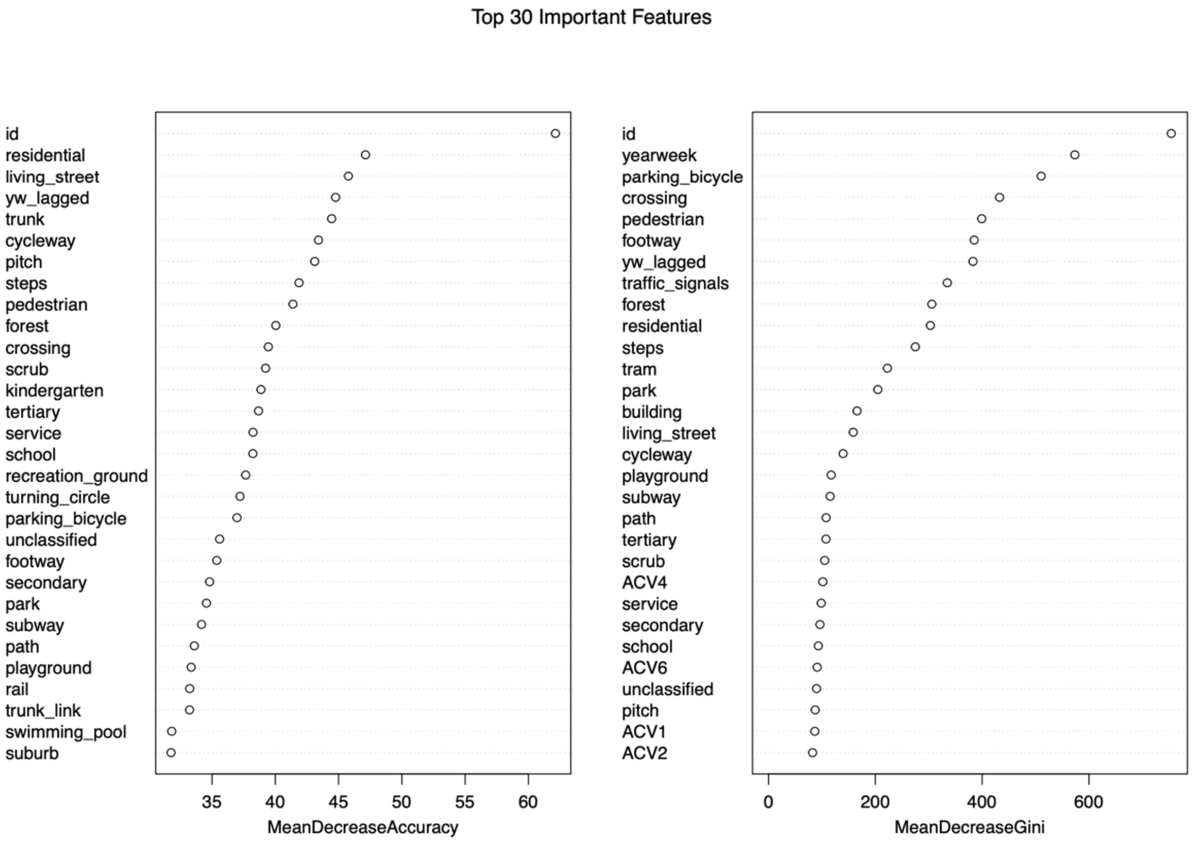

Figure 8: Random forests – 250x250m variable importance plot

500x500m variable importance plot

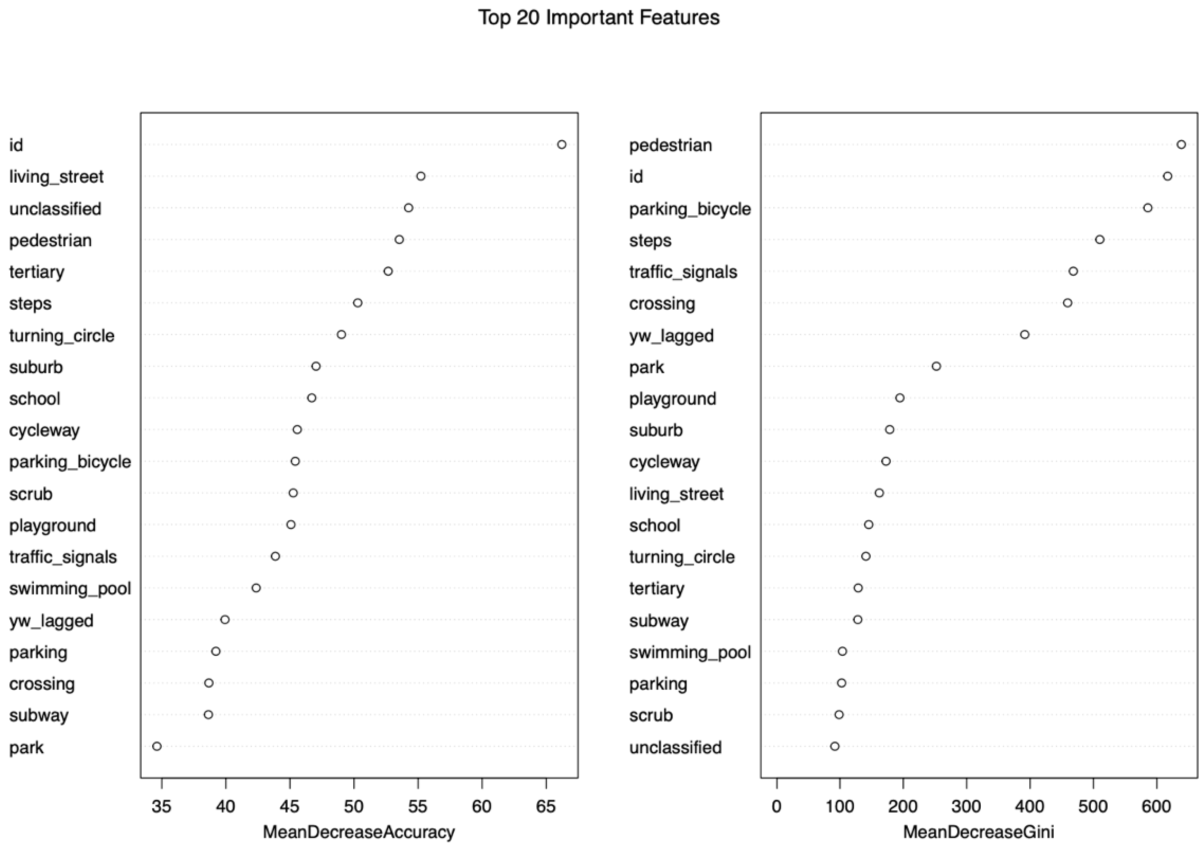

Figure 9: Random forests – 500x500m variable importance plot