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An Organised Analysis of Multiple-Scale Spatial-Temporal Crime Prediction Techniques

Techniques for Preventing Crime

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Abstract: Criminal activity is consistently one of the most significant societal issues, endangering both individuals and public safety. The government, police, and public may all implement efficient crime prevention strategies with the aid of accurate crime prediction. This study reviews the literature on crime prediction methodically from several temporal and spatial angles. With an emphasis on prediction techniques, we provide an overview of the state of crime prediction research as of right now from four angles: prediction content, crime kinds, methodology, and assessment. Crime prediction on different temporal and spatial scales may be broken down into three categories: micro-, meso-, and macro-level prediction for spatial crime, and short-, medium-, and long-term prediction for temporal crime prediction. A range of assessment criteria and crime prediction techniques are also compiled, and various models and prediction techniques are contrasted and assessed. After reviewing the literature, it was discovered that there are still a lot of gaps in the knowledge base. These gaps include: (i) the difficulty of effectively handling data sparsity; (ii) the lack of predictive model practicality, interpretability, and transparency; (iii) the evaluation system's relative simplicity; and (iv) the paucity of research on the application of decision-making. To address the issues mentioned above, the following recommendations are made in this regard: In order to deal with sparse data, (i) transformer learning technology is used; (ii) model interpretation techniques, such as Shapley additive explanations (SHAPs), are introduced; (iii) a set of standard evaluation systems for crime prediction at various scales is established in order to standardise data use and evaluation metrics; and (iv) reinforcement learning is integrated in order to achieve more accurate prediction while encouraging the transformation of the application results.

***KeyWord* - Crime; Public Security; Multi-Scale; Spatial-Temporal; Crime Prediction.

I. Introduction

Crime is an ongoing, dynamic, and intricate process with intricate relationships to location, time, and the environment. The majority of crimes, including theft and robbery, have a close relationship with the location and timing of their occurrence. It has been demonstrated that there is some pattern and aggregation in the temporal and spatial distribution of crime rather than it being random. The locations of crimes are more concentrated, creating "crime hotspots." Consequently, this allows for the prediction of crime. Today, preventing and combatting crime requires accurate and reliable crime prediction. It not only lowers crime rates, lessens financial losses, and enhances public safety, but it also aids in the efficient and responsible use of police resources by governments and law enforcement organisations.

The primary sources of data used in crime prediction include historical crime, environmental, socioeconomic, and network social data. From these sources, crime-related variables are extracted to forecast the likelihood of crime within a certain geographic and temporal range in the future. This makes it possible for police agencies to proactively deploy police resources and carry out targeted preventive and control measures for a given period of time and place. Examples of these include the deployment of reasonable and scientific patrol routes, the calculation of the required number of patrols, the identification of the best time for patrols, and the timely creation of arrest plans. On the basis of this, several academics have made considerable contributions to the domains of crime simulation, crime hotspot mapping, and crime prediction, leading to notable advancements.

By examining the most recent studies on temporal and geographical crime prediction, this study focuses on crime prediction techniques. The following is the primary work.

i. A thorough assessment of studies on crime prediction is conducted from a variety of temporal and geographical angles.
ii. A summary of popular assessment metrics and temporal and geographical crime prediction techniques is provided.
iii. The study's shortcomings are examined, and logical recommendations for other research possibilities are given.

This review's remaining structure is set out as follows. The study methodology and a summary of the pertinent studies are presented in Section 2. The common criminal prediction techniques and assessment measures are covered in Section 3. The multi-scale temporal, spatial, and spatio-temporal crime prediction investigations are described in detail in Sections 4-6. These include the following: micro-, meso-, and macrolevel predictions for temporal crime prediction; short-, medium-, and long-term predictions for spatial crime prediction; and, as illustrated in Figure 1, the classification of spatio-temporal crime prediction as a permutation of temporal and spatial crime prediction classifications. The paper's conclusion and some recommendations for further research are included in the last part.

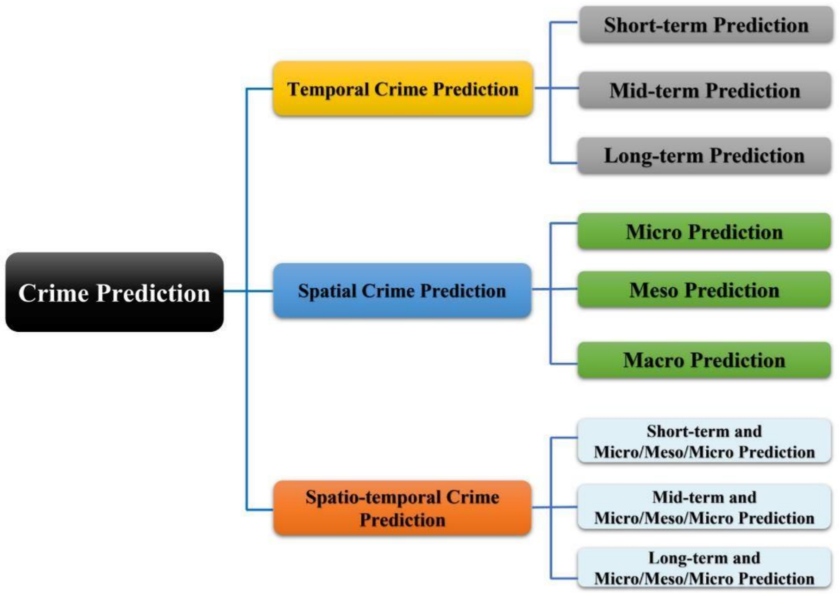

Figure I-1 multi-scale spatio-temporal crime prediction

II. Materials and Methods

2.1 Publications Sources

The preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines were adhered to in the collection and screening of literature for this study. Publications pertaining to "spatiotemporal crime prediction" from 2013 to 2022 were searched for and screened.

2.1.1 Publications Search

The preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines were adhered to in the collection and screening of literature for this study. Publications pertaining to "spatiotemporal crime prediction" from 2013 to 2022 were searched for and screened. Initially, we conducted a search for publications in the bibliographic databases "Web of Science (WOS)," "Institute of Electrical and Electronics Engineers (IEEE) Xplore," "Association for Computing Machinery (ACM)," and "China National Knowledge Internet (CNKI)" using the following keywords: crime prediction, forecasting crime, forecasting crime, spatio-temporal crime prediction, and temporal crime prediction." 12,579 articles in all were obtained; these came from 7517 databases in the “WOS” database, 1087 databases in the “IEEE” database, 3723 databases in the “ACM” database, and 252 databases in the “CNKI” database. The most recent search was carried out on April 28, 2023.

2.1.2 Publications Screening

The publications that were duplicates, outside the parameters of the publishing kinds (conference, journal, and thesis), or without authorization to view and download were eliminated in the following stage. After that, we went over the titles, abstracts, major bodies, and findings of the remaining literature to weed out those that didn't relate to the subject, were poorly written, or had no historical significance. Following filtering, 79 publications were still present, of which 16 were in Chinese and 63 were in English.

2.2 Research Overview

2.2.1 Research Content

Figure shows illustrates that of the 79 papers that were chosen, 7 were reviews, 28 were on temporal crime prediction, 8 were on spatial crime prediction, and 36 were on spatio-temporal crime prediction. Predicting crime trends in a given area over time without taking crime hotspots or geographical distribution into account is known as "temporal crime prediction." The fact that most spatial crime prediction research typically combines particular time and crime types for analysis and prediction, which is then transformed into spatio-temporal crime prediction research, explains why there are comparatively few publications on spatial crime prediction.

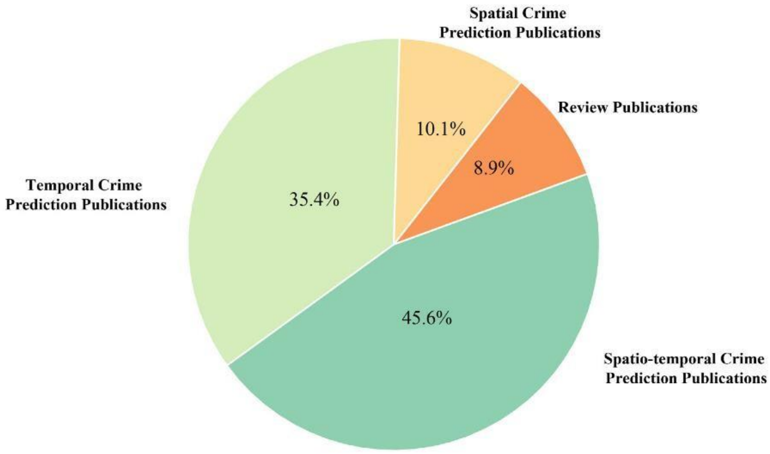

Figure II-1 Distribution of crime prediction publications

2.2.2 Types of Crime Predicted

Regarding the categories of crimes anticipated, typical categories comprise, among others, robbery, motor vehicle theft (8 publications), burglary, theft, assault, and homicide. One advantage of having so much crime data available for study is that doing research on crime prediction is much simpler. Conversely, the study around these kinds of crimes is more applicable and significant since they are intimately linked to everyday life. Furthermore, for the purpose of predicting assault and battery crimes, neural networks, ensemble models, and other frameworks are frequently employed. Predicting theft crimes often makes use of neural networks, ensemble models, different frameworks, and ARIMA models. Neural networks, ensemble learning, RF models, and other frameworks are frequently utilised for burglary crime prediction.

2.2.3 Evaluation Metrics

Evaluation metrics are crucial for assessing model performance in crime prediction research. The top five evaluation metrics used in crime prediction research include root mean square error (RMSE), predictive accuracy index (PAI), mean absolute error (MAE), accuracy, and area under curve (AUC). RMSE, MSE, and accuracy are commonly used for temporal crime prediction research, while PAI is commonly used for spatial crime prediction. In future crime research, RMSE can be selected as the main evaluation metric for temporal crime prediction, while PAI can be used as the main evaluation metric for spatial crime prediction. The trend of crime prediction research is focusing on spatial-temporal crime prediction, with property crime and violent crime being the main types predicted. Complex ensemble models and random forest models are increasingly used for prediction methods.

III. Crime Prediction Methods and Evaluation Metrics

3.1 Machine Learning

Artificial intelligence (AI), biology, chemistry, materials science, agriculture, architecture, meteorology, natural language processing (NLP), and computer vision have all benefited greatly from machine learning (ML) advancements over the last 20 years. Machine learning (ML) is pervasive in our daily lives, influencing everything from facial recognition, spam categorization, and property price prediction to autonomous cars. Machine learning (ML) is the process of continually feeding data into models to help them understand any possible rules that may be there. Once trained, these models may be used to predict, classify, or cluster new data. Three major categories for machine learning exist: semi-supervised, unsupervised, and supervised learning. Among them, unsupervised learning concentrates on resolving issues like association analysis and clustering, whereas supervised learning mostly addresses classification and regression difficulties. Between supervised and unsupervised learning lies semi-supervised learning, which may be used to accomplish a range of objectives including dimensionality reduction, regression, and classification. The most widely utilised techniques for predicting crimes nowadays include neural networks, ensemble algorithms, LR, and RF.

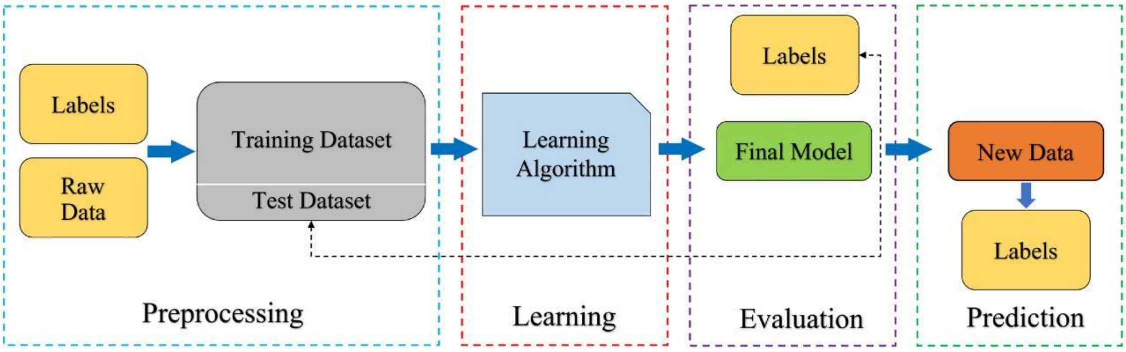

Figure III-1 Basic process of machine learning

3.2 Crime Mapping

Crime mapping is a crucial tool in police work, enabling the prediction of crime locations in the future. Two commonly used methods are KDE and RTM. KDE visualizes crime hotspots and predicts crime by generating a continuous, smooth surface map on a grid. It can also measure building density, predict stock risk, and detect crime hotspots. Parameters like grid cell size and bandwidth significantly impact KDE's accuracy. RTM is a geographic risk assessment method that identifies and predicts potential risk factors and their spatial impacts based on the landscape's characteristics. It estimates the probability of crime occurring in the area at a microlevel, aiding police agencies in developing targeted policing strategies and allocating resources to areas with higher risk. RTM is derived from environmental criminology and uses multiple landscape risk map layers to generate a comprehensive risk terrain map. Rutgers University has developed RTMDx software for identifying potential risk factors in high-crime areas. Combining RTM with KDE and combined analysis of case configurations improves prediction accuracy and interpretability.

3.3 Other Prediction Methods

Crime prediction research has utilized various models and techniques, including ARIMA, LASSO, and agent-based modeling (ABM). ARIMA is a time series prediction model that combines the AR and MA models. LASSO is a least absolute shrinkage and selection operator (LASSO) regression technique that uses the least squares method to prevent overfitting and improve generalization ability. It is commonly used for screening variables and risk analysis. ABM is a modeling and simulation technique that simulates individual behaviors, allowing for better understanding and prediction of criminal behavior. By simulating each agent's execution of rules and observing their behavior, ABM can help police and policymakers devise better strategies and tools to fight and reduce crime.

IV. Temporal Crime Prediction

According to varying time scales, temporal crime prediction may be divided into three categories: short-term, medium-term, and long-term. Hours, days, and weeks are the basis for short-term forecast, whereas months and quarters are the basis for medium-term projection. Most long-term predictions are made in terms of years. Depending on the components employed in the forecast, crime prediction approaches may be further categorised. These techniques might just use criminal data, or they might also use outside data. Figure displays a schematic that depicts the temporal crime prediction method.

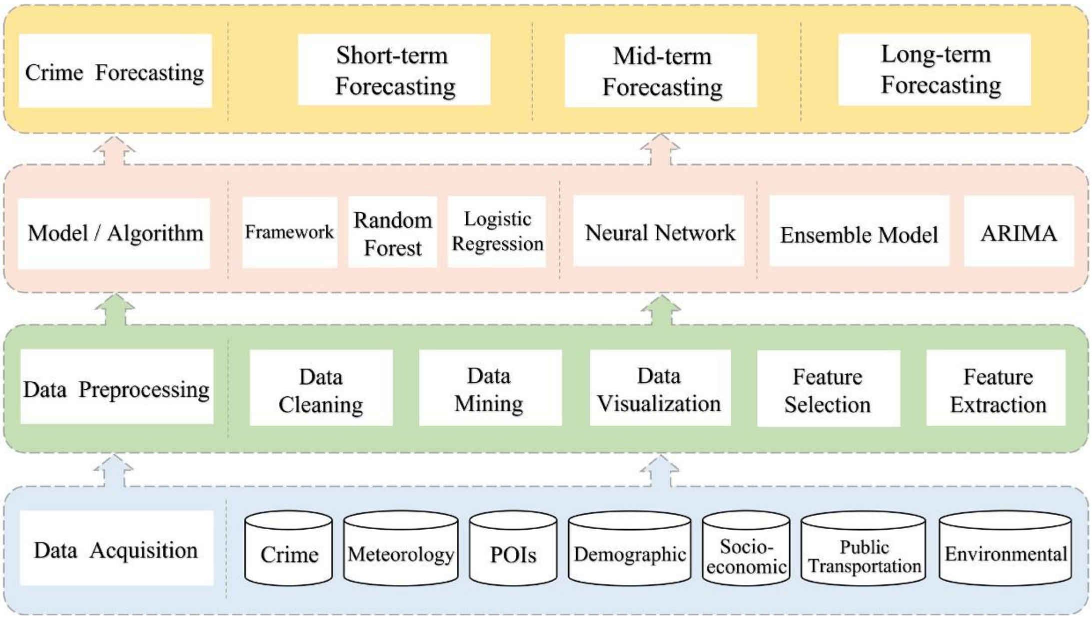

Figure IV-1 Temporal crime prediction process

4.1 Short-Term Prediction

The literature explores various models for short-term crime prediction, including the localized kernel density estimation (LKDE) model, neural network models, ensemble models, and the neural attentive framework for hour-level crime prediction (NAHC). LKDE is a model that uses historical crime data and social media with geo-tagged information, demographics, environment, and socio-economic data as covariates. Neural networks are used to predict crime counts for three crime types in Chicago and Portland using a combined CNN and RNN model. This model showed the best prediction performance, with an accuracy of 75.6% in Chicago and 65.3% in Portland. Ensemble models have been developed to predict crime numbers and crime risk levels, such as the hybrid LSTM and GCN model, ST–GCN. This model consists of three modules: spatio-temporal feature extraction, temporal feature extraction, and attention mechanism modules. It was used to predict burglary crimes in Boston and Chicago neighborhoods, with lower RMSE, MAPE, and R2 than other models. However, ML-based crime prediction models are less transparent and explanatory, leading to weak interpretability and reliability. To address this limitation, an interpretable prediction model based on the XGBoost and SHAP was proposed. This model predicts public theft at the XT police station with crime and environmental population data. The results showed an accuracy of 0.89 and a ROC of 0.586, with positive correlations between variables' contributions. The NAHC framework can effectively overcome the challenge of capturing spatio-temporal interactions between crimes occurring at different times and places, providing deeper insights into the spatio-temporal correlation of crime. The literature implemented hourly level crime prediction for Xiaogan City using the NAHC framework, demonstrating excellent performance in vehicle theft, assault, pickpocketing, and burglary.

4.2 Medium-Term Prediction

Medium-term prediction models include the latent Dirichlet allocation (LDA) model, DeepCrime framework, attention-based interpretable spatio-temporal network (AIST) framework, and integrated Laplace approximation (INLA) framework. The LDA model was used to predict crime trends in Chicago, with an average improvement of 15%. DeepCrime, a deep neural network framework, was developed to improve the performance and interpretability of crime prediction models. The AIST framework captures the spatiotemporal correlation of crime to achieve monthly or quarterly level prediction. The INLA framework was designed for monthly level prediction of burglary in 20 neighborhoods of Amsterdam city, using burglary as the dependent variable and land use, other crimes, and socioeconomics as covariates. The study found that the closeness of the street network, the number of retail stores, and street robberies were highly correlated with burglary, and the spatial and temporal distribution of burglary was concentrated.

4.3 Long-Term Prediction

The literature explores long-term prediction methods for urban crime, including the LASSO model, extremely randomized tree (extra trees) model, and ensemble models. The extra trees model, which has a higher accuracy rate (83%), was used to study factors influencing urban crime in China, such as living land area, cell phone usage, and employed population. The ensemble model, designed using an instance-based transformer learning setup, incorporated 19 features from six scenarios to train a GB classifier model. The

GB classifier model had the best performance. The literature also used RF, extra trees, and GB models for long-term crime prediction in New York City, using census, spatial, and temporal features extracted from geo-tagged human mobility data. The extra trees model predicted the best performance, and the model using human mobility data made better predictions than the census-based model. The RF regression model predicted the number of homicides in Brazil after 10 years with 97% accuracy. Urban indicators, such as unemployment, illiteracy, and male population, were identified as the most important factors affecting homicide.

4.4 Limitations of Temporal Prediction Research

Research on temporal crime prediction has made significant progress, moving from a single model to an integrated model and deep learning framework. This has improved prediction performance by capturing crime-related spatio-temporal characteristics. However, the current research still faces several challenges, such as data sparsity, insufficient practicality, interpretability, and transparency of the model. Data sparsity is a challenge as some areas have limited crime data, making it difficult to support crime prediction. Additionally, the granularity of time and space increases, leading to more irrelevant information and difficulty in accurately identifying and extracting crime-related features. Insufficient practicality, interpretability, and transparency of the model are also issues. ML-based prediction models often lack interpretability due to their "black-box" nature, making it difficult to evaluate a model based on accuracy alone. There is a need to introduce model interpretability methods to improve understanding of how the model's function. A single evaluation system is also needed, as the evaluation metrics and data used in these studies vary, making it difficult to judge the merits of the models accurately. A comprehensive evaluation system considering various data types and evaluation metrics is needed to truly judge the merit of the models. Lastly, there are limited studies on short-term crime prediction, as most studies focus on medium- and long-term crime prediction, which has a positive impact on macro-level policy making.

V. Spatial Crime Prediction

The projected region is frequently split into many grid units of various sizes, such as 200 m ~ 200 m or 150 m ~ 150 m, in spatial crime prediction. Prediction accuracy generally increases with the size of the spatial unit. Overly huge grid cells, however, do not correspond with the real patrol range of police personnel. As a result, crime spatial prediction may be categorised into three levels using the analytical hierarchy process (AHP) method: macro-, meso-, and micro-level predictions. The primary focus of micro-level prediction is on regions that are smaller than the current functional zoning. The functional zoning that now exists, such as census tracts, police districts, and neighbourhoods, is primarily covered by meso-level prediction. The majority of macro-level projections are made at the county, municipal, state, and federal levels.

5.1 Micro- and Meso-Level Prediction

Micro- and meso-level spatial crime prediction involves community, campus, street, and rural areas, such as street robbery and community burglary. Researchers have studied prediction in these geographical areas to address sparse urban street crime events. The grated localized diffusion network (GLDNet) was proposed as a graph-based deep learning framework to improve average hit rates, particularly in terms of street length coverage rate. Clustering methods were used to detect hotspots of wildlife poaching in the Tsavo ecosystem in Kenya. The aggregated neighborhood risk of crime (ANROC) measure was proposed to enable neighborhood-level prediction of violent crime rates. The ANROC measure was significantly and positively correlated with community violent crime, suggesting it helps to understand changes in neighborhood violent crime and achieve neighborhood-level violent crime predictions. The street robbery data from Little Rock, Arkansas, was used to assess the techniques, with the average PAI and recapture index (RRI) being the highest for KDE and RTM, indicating better prediction accuracy and higher prediction precision.

5.2 Macro-Level Prediction

Urbanization has led to an increase in crime, making it challenging for police to respond effectively. Predicting urban crime has become critical to combat this issue. The STDC detector, a spatio-temporal crime geographical displacement (STCD) detector, was used to study burglary in a large Chinese city, confirming the existence of crime geographic displacement and improving prediction accuracy. Regression-based modeling (RTM) was used to predict changes in crime distribution in large cities based on robbery data and land use data in Newark. The stochastic model showed the worst performance, while the integrated model had the best prediction. Combining event dependence and spatial influences can effectively improve the prediction of dynamic crime distributions. Agent-based models were applied to simulate the behavior and interactions of criminals and police officers to reduce crime rates. The results showed that agent-based models could effectively evaluate and predict criminal behavior and provide valuable recommendations for anti-crime policies. Improving community development and implementing safety measures could reduce crime likelihood, while increasing police presence or strengthening surveillance could enhance the probability of apprehending criminals. Deep learning frameworks have demonstrated promising results in predicting crime hotspots. Three different configurations of deep learning frameworks were proposed: spatial features first then the temporal (SFTT), temporal features first then the spatial (TFTS), and spatial and temporal features in two parallel branches (ParB). In Porto, Portugal, machine learning, topic modeling, and sentiment analysis were used to identify and predict crime patterns and hotspots. The random forest algorithm had the best prediction performance, with the emotional state reflected in tweets closely related to crime locations. A data-driven approach was applied to predict crime levels in the Greater London area, analyzing multiple heterogeneous datasets and selecting three regression algorithms as training models.

5.3 Limitations of Spatial Crime Prediction Research

Spatial crime prediction research has made significant progress in identifying potential risk factors and crime hotspots, while validating criminology theories. However, the field still faces challenges such as the quality of crime data, the availability of relevant urban features, and the integration of various data sources. There is a lack of research on decision-making applications, with some studies lacking practical support for assisted decision-making. This hinders the effectiveness of crime prevention strategies. The current research fails to consider the impact of criminal behavior patterns on crime prediction results, such as the presence of police on an offender's travel route. Future studies should aim to expand and advance crime mechanism research to improve the accuracy and applicability of crime prediction models. Unreasonable grid cell size is another issue in spatial crime prediction studies. Most studies employ grid cells with side lengths of 100 m, 150 m, and 200 m, which generally result in better prediction performance. However, the theoretical limit range of a police patrol is 150 m, which should be considered when adjusting grid size according to actual conditions and police patrol frequencies. Balancing prediction performance and practical application is crucial in optimizing the implementation of spatial crime prediction models.

VI. Spatial-Temporal Crime Prediction

The incorporation of criminal, location, and temporal data not only enhances forecast accuracy but also adds realism to implemented preventive and control measures. We offer an overview of the main spatio-temporal scales examined because there are a lot of ways that temporal and spatial crime forecasts may be made.

6.1 Short-Term and Micro-Level Prediction

For fine-scale (hourly and geographically tiny) crime prediction, the literature introduced an enhanced deep spatio-temporal 3D convolutional neural network (ST3DNet) architecture called ST3DNetCrime. When actual Los Angeles data was used for assessment, the outcomes shown that ST3DNetCrime—especially ST3DNetCrime-f—had superior prediction performance and resilience over the baseline models. This suggests that the optimum prediction performance can only be attained by extracting all the spatiotemporal elements from current and near-historical crime data as well as far-historical crime data.

6.2 Short-Term and Meso-Level Prediction

The RF model was used to predict short-term crimes in public places, including robbery, snatching, and public theft. The study area, XT Street, was divided into 369 grids based on historical crime rates. The model was constructed using historical crime data or environmental covariates. Control experiments were conducted, and results showed that spatial variations and environmental variables improved prediction precision, particularly in stable high-incidence grids.

6.3 Short-Term and Macro-Level Prediction

The literature has developed various regression models to predict residential and commercial break and entries (BNE) crimes in Vancouver, Canada. These models were used to visualize crime trends and spatial and temporal distributions. Residential BNEs had higher recidivism rates within 850 m and 1 day from the last crime location, while commercial BNEs had higher recidivism rates beyond 500 m and within 2 days from the last crime location. An "online" integrated graphical model based on attentional mechanisms was developed, which was able to predict the spatio-temporal distribution of daily urban crime more accurately than other models. The ST-Corking algorithm was used to detect the impact of potential offender activity on crime prediction. A spatio-temporal crime model was constructed using a collaborative training model and a CoBayes model to infer road-level crime risk. An application was developed to recommend the best risk-aware route. The literature also used ARIMA and KDE models to predict the spatial and temporal distribution of crime over 15 days. A TCP framework was constructed to capture the spatio-temporal correlation of urban data to predict crimes in New York City.

6.4 Medium-Term and Macro-Level Prediction

The literature has developed various models to predict crime events, including assault, property crime, and urban crime trends. The models were built using RTMDx and ArcGIS, with the highest prediction accuracy for assault. The study focused on property crime risk areas in Coral Gables, identifying high-risk areas like restaurants and grocery stores. An ensemble model based on logistic regression and neural networks was used to predict urban crime trends over two weeks and one month. A spatio-temporal kernel density estimation (STKDE) framework was developed to predict crime hotspots, with the highest average PAI value. The DNN tuning model was used to predict vehicle theft, with better performance than other models. A deep learning framework, DeepPrison, was developed for burglary prediction at different granular levels, extracting burglary features from historical crime data, socio-demographic data, and weather data. The model performed better than baseline models like DeepCrime at all granularity levels.

6.5 Long-Term and Meso-Level Prediction

This report examined property crimes in the York region of Ontario, Canada in 2006 and 2007, validating the efficacy of Bayesian spatial-temporal modelling in analysing crime patterns and hazards in small regions. The findings showed that the Bayesian spatial-temporal model is capable of accurately predicting trends in property crime in limited regions and locating hotspots and colds for criminal activity. This has applications for how law enforcement resources are allocated and strategies are created.

6.6 Long-Term and Macro-Level Prediction

The literature explores the impact of population density on crime prediction using hyper-ensemble models, focusing on urban crime. The model predicts crime trends in low-density areas, providing support for public decision-making. A study in Wuhan, China, found that residential burglary is positively correlated with internet cafes, properties, unemployment rates, and the number of internet cafes. In the US, an ensemble model predicts crime totals, with 77% accuracy for violent and 73% accuracy for property crimes. The model's MAE and R2 improved significantly compared to other models, indicating its potential for offsetting crime sparsity.

6.7 Limitations of Spatial-Temporal Crime Prediction Research

Spatial-temporal crime prediction combines time and space scales, making research more relevant. However, it exposes complex problems related to time and space scales. Spatio-temporal correlation and heterogeneity are challenges in traditional machine learning models. To address these, jointly model time and space, introduce self-supervised learning mechanisms, and design multi-task learning modules to capture spatiotemporal correlation and heterogeneity separately.

VII. Conclusion

The development of big data technology has revolutionized spatio-temporal crime prediction, but some methods may not fully address the complex nature of contemporary crime. This paper proposes practical solutions to address these challenges, focusing on data sparsity, model interpretability, and data use and evaluation systems. Data sparsity is a common challenge in the crime prediction field, limiting the accuracy and generalizability of prediction models. Transfer learning techniques can be used to address this issue by applying information and knowledge from existing domains to related domains. Feature selection, feature extraction, and cross-validation methods can also be employed to optimize the performance and efficiency of spatial crime prediction models. Model interpretability methods, such as LIME and SHAP models, can enhance the understanding and trustworthiness of prediction models. Establishing a set of data use and evaluation systems for multiple scales promotes accuracy, consistency, and interoperability. Integrating crime simulation and reinforcement learning technologies can enhance decision-making applications in the spatial crime prediction field, enabling more efficient and targeted crime prevention and control measures. In conclusion, combining simulation modeling, deep reinforcement learning, and crime prevention strategies can enhance the implementation and effectiveness of spatial crime prediction models, contributing to more efficient and targeted crime prevention and control measures.

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