A Study on Crime Hotspot Detection and Prediction Using Spatial-Temporal Modeling for Safe Navigation

Riya Bansilal Mulani, Anushka Biswas, Jaypriya J, Vinay M[1]
[1]*Computer Science Department, CHRIST University Bangalore Yeshwantpur Campus, Karnataka.*

Abstract- **This research explores advanced methods for crime hotspot detection and forecasting using spatial-temporal modeling and machine learning techniques. We employ the Space-Time Permutation Model (STPM) via SatScan to classify crime hotspots in Pune city, India, comparing its effectiveness with Kernel Density Estimation (KDE) and Getis-Ord Gi* statistics. While these approaches produce generally similar outcomes, minor discrepancies suggest the need for improved detection strategies. Additionally, we apply machine learning algorithms, including Logistic Regression, SVM, and Random Forest, to crime datasets from Chicago and Los Angeles to enhance prediction accuracy. Our findings highlight the potential for integrating real-time data and predictive models to optimize law enforcement resource management and improve future crime prevention efforts.**

Keywords- **Crime hotspot detection, spatial-temporal modeling, Space-Time Permutation Model, SatScan, Kernel Density Estimation, Getis-Ord Gi* statistic, machine learning, crime prediction, Logistic Regression, SVM, Random Forest, ARIMA, LSTM, real-time data, law enforcement**

I. INTRODUCTION

Crime analysis and prediction have become increasingly vital research areas, driven by the urgent need for more effective crime prevention strategies and the optimization of law enforcement operations. As urbanization accelerates and populations expand, the complexity and frequency of criminal activities pose significant challenges to public safety. In response, this research investigates the application of advanced spatial-temporal models and machine learning techniques, specifically targeting the improvement of crime hotspot detection and forecasting. [2, 12, 15, 16, 18, 21, 24, 26, 28, 32, 36, 37, 41] These enhancements are designed to assist law enforcement agencies in making data-driven decisions regarding resource allocation, ultimately enabling more proactive crime prevention efforts. The study concentrates on the city of Pune, Maharashtra, India, employing the Space-Time Permutation Model (STPM) within SatScan, a powerful open-source tool renowned for its spatial- temporal analysis capabilities. The study compares the effectiveness of STPM with established methods like Kernel Density Estimation (KDE) and the Getis-Ord Gi* statistics, both of which are commonly used to identify high-crime areas. [2] In addition to hotspot detection, the research extends to predictive crime analysis, utilizing an array of machine learning algorithms—Logistic Regression, Support Vector Machines (SVM), Naïve Bayes, K-Nearest Neighbors (KNN), Decision Trees, Multi-Layer Perceptron (MLP), Random Forest, and XGBoost—applied to crime datasets from Chicago and Los Angeles. The ultimate objective is to enhance the accuracy and reliability of crime forecasting models. It systematically compares the running time performance of various space-time models and machine learning algorithms, in order to find out which ones are better for near real-time crime analysis in urban environments; it also adds value to this area by testing new data sources but including traditional techniques so as more precise (and actionable) results can be obtained. [3, 11, 19, 23, 25, 28, 30, 33, 37, 42]

II. BACKGROUND

In all urban well-being and law implementation, crime investigation is turning out to be a major component. We have increasingly focused on discovering the right techniques for predicting criminal activities. One of the primary areas of focus in this area is identifying crime hotspots, or places that experience a significant amount of criminal activity to better allocate resources for law enforcement agencies and enable targeted crime prevention efforts. In this background study, we introduce the essential methodologies for analyzing crime—in particular spatial–temporal modeling and machine learning techniques as well as relate these methods to research on crime data. Literature on the review emphasizes these methodologies as important in progressing crime analysis.

Techniques in spatial- temporal modeling are key for studying the distribution of crime events over time and space, providing indications on emerging patterns or trends. The Space-Time Permutation Model (STPM) implemented through SatScan software is commonly used; a unique feature of the STPM model, over conventional statistical modeling methods to examine crime clustering patterns [8], detects clusters of events close in both time and space—suitable for identifying newly detect emerging crime hotspots. This includes using a Kernel Density Estimation (KDE) model to estimate the probability density function for crime events, and employing Getis-Ord Gi*, an approach in spatial statistics that can be used as a local indicator of clusters High/Low values. Machine learning techniques are also used for crime analysis, but the algorithms like Logistic Regression, Support Vector Machines (SVM), Naïve Bayes, and Random Forest offer predictive capabilities that surpass traditional methods. These algorithms are applied to historical crime data to forecast future events, with time-series analysis methods such as ARIMA and LSTM providing valuable insights into crime trends over time.

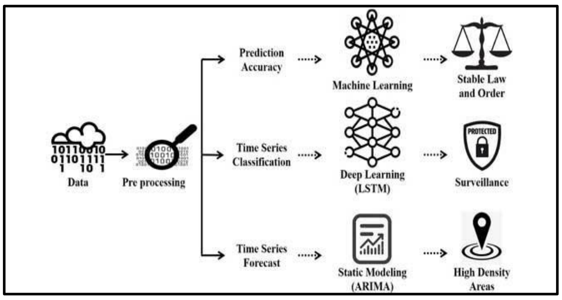

Figure 1: Framework Analysis

The diagram gives a way in which data gets pre-processed and analyzed using machine learning, deep learning (LSTM) and ARIMA models. These techniques are implemented in order to provide high prediction accuracy for the police, better surveillance of regions with dense populations and more efficient management of areas where human probabilities may be higher.

III. LITERATURE REVIEW

Spatial-temporal modeling in crime analysis, as a general practice Skiles et al., 2017; Liu & Eckberg, 2006). Kulldorff et al. In 1998, Kulldorff et al introduced a software tool for spatial, temporal, and space-time scan statistics called SatScan that has subsequently been widely adopted to detect crime hotspots. Studies such as by Nakaya and Yano (2010) have demonstrated the utility of STPM in detecting important crime clusters, especially those among urban areas with a changing pattern of crimes.

Kernel Density Estimation (KDE) is also a common technique for mapping crime hotspots. Chainey et al. This study compared KDE with two other hotspot mapping methods and concluded that the visualization of crime density is both intuitive for end users, resulting in increased usability benefits, as well as reflective of an approach to strategic policing. However, the literature also highlights some limitations of KDE. In particular, its dependence upon bandwidth selection can have a large effect on results (Levine 2013). [21, 28, 32]

Getis-Ord Gi* has been employed in numerous studies to detect spatial clusters of crime. Ord and Getis (1995) first proposed the statistic, which has since been applied in several criminological studies to locate areas of high and low crime activity. For instance, Ratcliffe (2010) used Getis-Ord Gi* to analyze burglary patterns in Philadelphia, highlighting its effectiveness in understanding the spatial distribution of crime. [3, 11, 19, 23, 25, 28, 30, 33, 37, 42]

Recent research has been also conducted in the area of crime analysis to improve predictive machine learning models. Wang et al. (2017) studied the Logistic Regression, SVM and Random Forest on predicting crime hot spots finding that ensemble methods like RF tends to outperform single classifiers. For the rest of flow cytometry, we refer to studies such Boulton et al., (2019) were one of the first to point out that using real-time data would significantly increase model accuracy.

Besides, wise time-series analysis employing ARIMA and LSTM models have been developed to predict crime trends. Bogomolov et al. The previous studies by Lum et al. (2015) have shown that ARIMA has a great utility in short-term forecasting of crime trends, although recent developments in deep learning such as LSTM model, specially for sequential data like the crime condition over time frames it reflect promising success to capture complex temporal dependencies exist within the dataset (Zhang et al., 2018).

The literature highlights a common recognition that spatial-temporal models should be combined with machine learning to produce higher quality and relevant crime predictions. There is a lot of room to improve on these still, though — especially in the realm of hyperparameter optimization and new source data integration.

IV. PROPOSED IDEA

The survey included a number of crime prediction models, such as machine learning algorithms: Logistic Regression, Support Vector Machines, Naive Bayes, K-Nearest Neighbor, Decision Trees, Random Forest, and XGBoost. In contrast, these algorithms are well recognized for their potential to handle complicated datasets and expose hidden trends, thus making them suitable for crime prediction. The survey also reviewed time-series analysis models like ARIMA (Autoregressive Integrated Moving Average) and Long Short-Term Memory (LSTM) networks to see how effective these models are when dealing with the important task of forecasting crime trends. The potential of using some computer vision's power, like YOLO Object Detection, to enhance classification and analysis of crime data, was investigated. This would really matter in those scenarios where visual data from surveillance cameras or street views is key for providing context.[4]

The survey pointed towards the critical outcome of the effectiveness of various methods for hotspot detection, including the Space-Time Permutation Model (STPM), the Kernel Density Estimation (KDE), and the Getis-Ord Gi* statistics. These methods are important in the identification of spatial and temporal crime clusters that are significant in pinpointing high-risk areas that could be identified in a navigation system. The measurements using these methods showed fairly consistent observations, although some inconsistencies were noticed in a few sensitive areas. These discrepancies were as a result of the selected significant clusters and general limitations of the methods in other contexts. This paper avails optimizing the integration of these techniques into Google Maps by addressing the observed discrepancies and adjusting the models for better accuracy. [3, 11, 19, 23, 25, 28, 30, 33, 37, 42]

V. METHODOLOGY

The methodology utilized for the survey was a stringent and organized review of already available literature, including the synthesis of findings from numerous studies that used these models on the prediction of crime and hotspot detection. A comparative study was performed on the performance of these models' using metrics like accuracy, precision, recall, and F1-score. The potential of data fusion was underlined by the survey, which consolidates real-time data streams with historical crime records to give more accuracy and reliability in the predictions. It delves into how spatial and temporal factors influence the workings of such models and gives recommendations on how best to improve their systems. Such optimization would be about tuning the parameters of the model while bringing in context variables such as socio-economic indicators and environmental factors to boost the predictive power. The data for this survey originates from a variety of sources, thus allowing judgment of the proposed methodologies in broader contexts. The datasets used in the research include major

U.S. cities like Chicago and Los Angeles, and the publicly available Indore Police Crime dataset from India. It will also take into account the urban environment metrics, which allow one to take into account the characteristics of the environment, such as building density, street layout, and population demographics—all these features have a great impact on the criminality in one area. These data, after vigorous preprocessing that included feature engineering, normalization, and time series decomposition, were prepared for the process of model training and testing. Their performance was tested comprehensively and compared in different urban contexts to see which model is more effective in predicting crime hotspots. Key aspects of the proposed safety feature include a viewable visualization of forecasted crime hotspots, done through such techniques as heatmaps and cluster analysis in the creation of instinctive and action-oriented visual representations. All such visualizations would overlay Google Maps, sharing clear and immediate information with users as to the safety of their surroundings and helping them navigate urban environments more safely. [all]

VI. DISCUSSION

This research explores advanced methods for detecting and forecasting crime hotspots using spatial-temporal modeling and machine learning techniques. In this context, the present study exploits the STPM approach through the SatScan model for locating the crime hotspots located within the city of Pune, India. The relative efficacy of this method is compared with at least two other methods in use currently: KDE and the Getis-Ord Gi* statistics. Though all of these approaches come out with roughly similar results, minor differences do suggest the likelihood of scope in strategies for enhancement in detection.

Furthermore, the study has tested, using the datasets of criminals obtained in both Chicago and Los Angeles, the predictive accuracy of these algorithms in terms of Logistic Regression, Support Vector Machine, and Random Forest. The findings underline that these types of predictive modeling have the potential to boost the predictions of criminal activities and lead to better resource management on the part of the department of law enforcement.

In this regard, the study concludes recommending advanced crime prediction methodologies and hotspot detection that could be incorporated into a platform such as Google Maps for data-driven, safe navigation. The literature review established, based on growing urbanization and concurrent increase in crime rates in metropolitan areas, that there is a requirement for innovative solutions. This would facilitate users to turn on real-time alerts on high-risk areas within navigation tools such as Google Maps, so they can revise their travel decisions to be safer.

Second, the paper also presents a framework upon which these models would actually be infused within the Google Maps ecosystem to make them more effective in crime prevention and resource allocation.

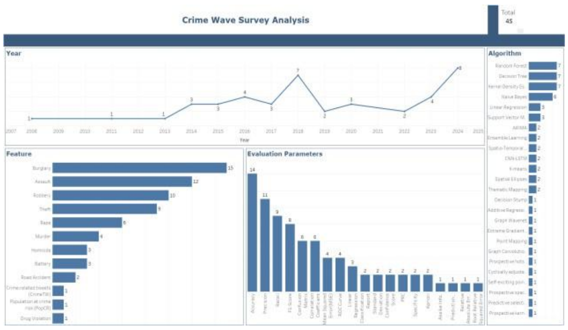

Figure 2: Crime Hotspot Dashboard

The tabular data is visualized and represented with the use of tableau dashboard as it is a snapshot shown in [Figure 2]. It is further elaborated and discussed for each visual in detail.

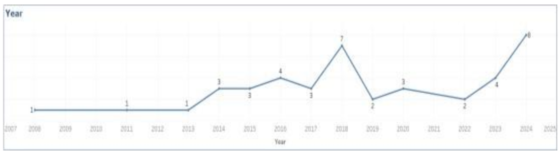

Figure 3: Research Publication Trend

The data in [Figure 3] reveals an initial slight increase in research from 2007 to 2010. Between 2010 and 2020, the number of publications fluctuated, marked by peaks and troughs. However, from 2020 onwards, there is a notable upward trend, with a particularly sharp rise in 2023.

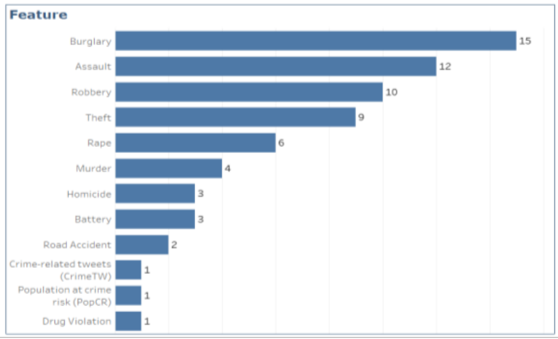

Figure 4: Types of Features

Data in [Figure 4] is particularly discussing how the research papers have identified particular features from a crime dataset. Key observations in [Figure 4] include that burglary is the most prevalent crime, highlighting significant concerns about property safety. Assault and robbery are also common, indicating a prevalence of violent crimes. Other serious offenses include theft, rape, murder, and homicide. Battery and road accidents point to potential physical harm, while crime-related tweets and population risk offer insights into public perception and vulnerability. Additionally, drug violations signal concerns about substance abuse-related crime.

Result perspective graph is illustrated as types of evaluation parameters used across numerous research papers, journals and articles as it would help in understanding accuracy of results.

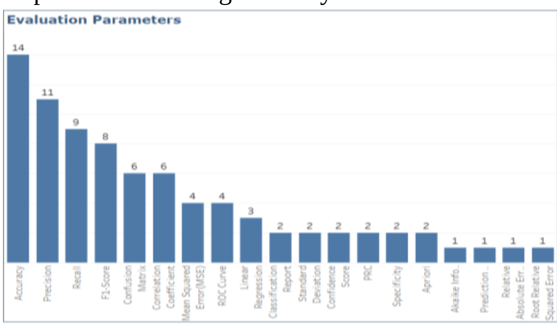

Figure 5: Types of Evaluation Parameters Used

Key observations from [Figure 5] include that Accuracy, Precision, Recall, and F1-Score are the most emphasized metrics, likely due to their common use in model evaluation. Metrics like Confusion Matrix, Correlation Coefficient, and Mean Squared Error are clustered together, suggesting they are related or used in similar contexts. Conversely, ROC Curve, Linear Regression, and Classification Report appear less frequently used or considered less important, based on their lower positions in the chart.

Methodology perspective graph is illustrated using types of algorithms implemented across numerous research papers, journals and articles as it would help us understand a particular type of methodology that is widely used.

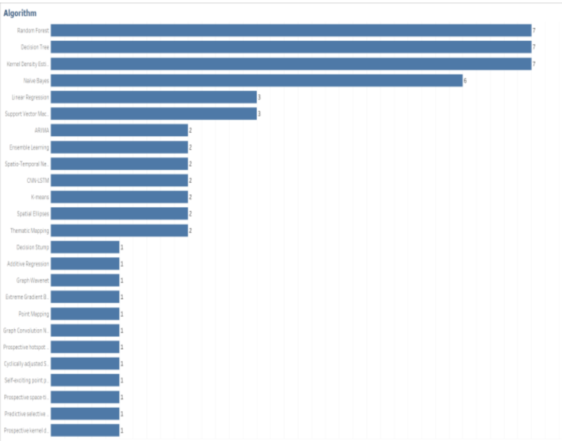

Figure 6: Types of Algorithms Implemented

The data in [Figure 6] shows that Random Forest, Decision Trees, and Kernel Density Estimation (KDE) are the most popular algorithms. Algorithms such as Spatial Clustering and K-means are grouped together, indicating they may be used in similar contexts for crime hotspot detection. Additionally, CNN-LSTM and Spatio-Temporal Networks appear to be gaining traction, likely due to their effectiveness in handling complex spatial-temporal data.

VII. CONCLUSION

In conclusion, this research has meticulously examined the integration of crime prediction methodologies into navigation systems, designed to enhance user safety. Through a thorough exploration of relevant applications and methodologies, including machine learning and spatial-temporal models, the study has demonstrated the potential of a data-driven solution to revolutionize urban navigation by offering real-time, safety-oriented features. The findings, supported by comprehensive analysis and visual insights, highlight the significant impact this innovation could have on public safety. Future work will focus on refining these methodologies and further enhancing the integration of real-time crime data into navigation systems.

REFERENCES

[1] McClendon, Lawrence, and Natarajan Meghanathan. "Using machine learning algorithms to analyze crime data." Machine Learning and Applications: An International Journal (MLAIJ) 2.1 (2015): 1-12.

[2] Mondal, Saswati, Dharmendra Singh, and Rakesh Kumar. "Crime hotspot detection using statistical and geospatial methods: a case study of Pune City, Maharashtra, India." GeoJournal 87.6 (2022): 5287-5303.

[3] Safat, Wajiha, Sohail Asghar, and Saira Andleeb Gillani. "Empirical analysis for crime prediction and forecasting using machine learning and deep learning techniques." IEEE access 9 (2021):70080-70094.

[4] Singh Bhati, Vikramaditya, Sourabh Tiwari, and Jaswant Mandloi. "Machine learning and deep learning integrated model to predict, classify and analyze crime in indore city." Proceedings of Recent Advances in Interdisciplinary Trends in Engineering & Applications (RAITEA) (2019).

[5] Tabarej, Mohd Shamsh, et al. "Graph-Based Hotspot Detection of Socio-Economic Data Using Rough-Set." Mathematics 12.13 (2024): 2031.

[6] Narasapuram, Penchalaiah, and Vishnu Vardhan Redddy Putha. "Machine Learning Meets Crime Prevention: A Stacked Generalization Approach for Identifying High-Risk Zones."

[7] Barbadekar, Ashwini, Akshata Kodak, and Omkar Kulkarni. "Real Time Alert System based on Crime Area Mapping." 2024 IEEE 9th International Conference for Convergence in Technology (I2CT). IEEE, 2024.

[8] Hamim, Omar Faruqe, and Satish V. Ukkusuri. "Towards safer streets: A framework for unveiling pedestrians' perceived road safety using street view imagery." Accident Analysis & Prevention 195 (2024): 107400.

[9] Bediroglu, Gamze, and Husniye Ebru Colak. "Predicting and analyzing crime—Environmental design relationship via GIS-based machine learning approach." Transactions in GIS (2024).

[10] Khan, Muzammil, Azmat Ali, and Yasser Alharbi. "Predicting and preventing crime: a crime prediction model using san francisco crime data by classification techniques." Complexity 2022.1 (2022): 4830411.

[11] Cesario, Eugenio, Paolo Lindia, and Andrea Vinci. "Multi-density crime predictor: an approach to forecast criminal activities in multi- density crime hotspots." Journal of Big Data 11.1 (2024): 75.

[12] Hashim, Hasranizam. "Crime Prediction Using Geospatial Intelligence System for Crime Preventing." Journal of Contemporary Issues and Thought 14.1 (2024): 54-62.

[13] P., Abhishek., Pallavi, Wankhede. (2022). Crime Prediction using Machine Learning. doi: 10.1109/ICETEMS56252.2022.10093303

[14] Atut, Pindarwati., Arie, Wahyu, Wijayanto. (2019). Personalized safety route recommender application using integrated urban crime hotspot data. doi: 10.1117/12.2547331

[15] Sampurna, Raha. (2023). A Novel Spatio-Temporal Model for Crime Hotspot Identification and Prediction. doi: 10.1007/978- 981-99-0838-7_40

[16] Araújo, Júnior., Adelson, Dias, de. (2019). Predspot: predicting crime hotspots with machine learning.

[17] Suryawanshi, Sejal. "Crime Predictive Model for Hotspot Mapping." International Journal For Science Technology And Engineering, undefined (2024). doi: 10.22214/ijraset.2024.63305

[18] Spencer, Chainey., Lisa, Tompson., Sebastian, Uhlig. (2008). The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime. Security Journal, doi: 10.1057/PALGRAVE.SJ.8350066

[19] R, Nivetha., C., Meenakshi. "Predicting Crime Hotspots using Machine Learning Techniques." International Journal of Advanced Research in Science, Communication and Technology, undefined (2024). doi: 10.48175/ijetir-1229

[20] Tugrul, Cabir, Hakyemez., Bertan, Badur. "Incorporating park events into crime hotspot prediction on street networks: A spatiotemporal graph learning approach." Applied Soft Computing, undefined (2023). doi: 10.1016/j.asoc.2023.110886

[21] Tugrul, Cabir, Hakyemez., Bertan, Badur. "Incorporating park events into crime hotspot prediction on street networks: A spatiotemporal graph learning approach." Applied Soft Computing, undefined (2023). doi: 10.1016/j.asoc.2023.110886

[22] Satvik, Shukla., Hari, Purnapatre., Gitalee, Jadhav., Rasika, Gohokar. (2020). Improving Women's Safety by accelerating Spatio Temporal Crime Prediction of Hotspots. International Journal of Computer Trends and Technology, doi: 10.14445/22312803/IJCTT-V68I12P108

[23] Shilpa, S., Deshmukh., B., Annappa. (2019). Prediction of Crime Hot Spots Using Spatiotemporal Ordinary Kriging. doi: 10.1007/978-981-10-8797-4_70

[24] Francisco, C., F., Nunes, Junior., Ticiana, L., Coelho, da, Silva., Jose, Florencio, de, Queiroz, Neto., José, Antônio, Fernandes, de, Macêdo., Wellington, Clay, Porcino. (2019). A Novel Approach to Approximate Crime Hotspots to the Road Network. doi: 10.1145/3356995.3364538

[25] Rhea, Singh., S., Raj, Mohan., Harsh, Pooniwala., Vignesh, Gokul., S., Shilpa. (2023). SafeMaps: Crime Index-Based Urban Route Prediction. Algorithms for intelligent systems, doi: 10.1007/978-981-99-4626-6_64

[26] Sankar, N., Nair., E., S., Gopi. (2020). Deep Learning Techniques for Crime Hotspot Detection. doi: 10.1007/978-981-15-0994-0_2

[27] Tahani, Almanie., Rsha, Mirza., Elizabeth, Lor. (2015). Crime Prediction Based On Crime Types And Using Spatial And Temporal Criminal Hotspots. arXiv: Artificial Intelligence, doi: 10.5121/IJDKP.2015.5401

[28] Sumanta, Das., Malini, Roy, Choudhury. (2016). A Geo-Statistical Approach for Crime hot spot Prediction. International journal of criminology and sociological theory,

[29] Yujie, Hu., Fahui, Wang., Cecile, C., Guin., Haojie, Zhu. (2018). A spatio-temporal kernel density estimation framework for predictive crime hotspot mapping and evaluation. Applied Geography, doi: 10.1016/J.APGEOG.2018.08.001

[30] M., N., Vijaya, Kumar., C., Chandrasekar. (2011). Spatial Clustering Simulation on Analysis of Spatial- Temporal Crime Hotspot for Predicting Crime activities. International Journal of Computer Applications,

[31] Gaurav, Hajela., Meenu, Chawla., Akhtar, Rasool. (2020). A Clustering Based Hotspot Identification Approach For Crime Prediction. Procedia Computer Science, doi: 10.1016/J.PROCS.2020.03.357

[32] Yong, Zhuang., Matthew, Almeida., Melissa, Morabito., Wei, Ding. (2017). Crime Hot Spot Forecasting: A Recurrent Model with Spatial and Temporal Information. doi: 10.1109/ICBK.2017.3

[33] George, Mohler. (2014). Marked point process hotspot maps for homicide and gun crime prediction in Chicago. International Journal of Forecasting, doi: 10.1016/J.IJFORECAST.2014.01.004

[34] Tahani, Almanie., Rsha, Mirza., Elizabeth, Lor. (2015). Crime Prediction Based On Crime Types And Using Spatial And Temporal Criminal Hotspots. arXiv: Artificial Intelligence, doi: 10.5121/IJDKP.2015.5401

[35] Sumanta, Das., Malini, Roy, Choudhury. (2016). A Geo-Statistical Approach for Crime hot spot Prediction. International journal of criminology and sociological theory,

[36] Yujie, Hu., Fahui, Wang., Cecile, C., Guin., Haojie, Zhu. (2018). A spatio-temporal kernel density estimation framework for predictive crime hotspot mapping and evaluation. Applied Geography, doi: 10.1016/J.APGEOG.2018.08.001

[37] Chunfa, Xu., Xiaoyang, Hu., Anqi, Yang., Yimin, Zhang., Cailing, Zhang., Yufei, Xia., Yanan, Cao. (2020). Crime Hotspot Prediction Using Big Data in China. doi: 10.4018/978-1-7998-0357-7.CH019

[38] Niyonzima, Ibrahim., Shuliang, Wang., Boxiang, Zhao. (2019). Spatiotemporal Crime Hotspots Analysis and Crime Occurrence Prediction. doi: 10.1007/978-3-030-35231-8_42

[39] Spencer, Chainey. (2014). Examining the extent to which hotspot analysis can support spatial predictions of crime.

[40] Monsuru, Adepeju., Tao, Cheng. (2017). Determining the optimal spatial scan of Prospective space-time scan statistics (PSTSS) for crime hotspot prediction.

[41] Ya, Han., Yujie, Hu., Haojie, Zhu., Fahui, Wang. (2023). A cyclically adjusted spatio-temporal kernel density estimation method for predictive crime hotspot analysis. Annals of GIS, doi: 10.1080/19475683.2023.2166584

[42] Monsuru, Adepeju., Gabriel, Rosser., Tao, Cheng. (2016). Novel evaluation metrics for sparse spatio-temporal point process hotspot predictions-a crime case study. International Journal of Geographical Information Science, doi: 10.1080/13658816.2016.1159684

[43] Alina, Ristea., Ourania, Kounadi., Michael, Leitner. (2018). Geosocial media data as predictors in a GWR application to forecast crime hotspots. doi: 10.4230/LIPICS.GISCIENCE.2018.56

[44] Hajela, Gaurav, Meenu Chawla, and Akhtar Rasool. "A clustering based hotspot identification approach for crime prediction." Procedia Computer Science 167 (2020): 1462-1470.

[45] Alves, Luiz GA, Haroldo V. Ribeiro, and Francisco A. Rodrigues. "Crime prediction through urban metrics and statistical learning." Physica A: Statistical Mechanics and its Applications 505 (2018): 435-443.

[46] Xu, Yanqing, et al. "The impact of street lights on spatial-temporal patterns of crime in Detroit, Michigan." Cities 79 (2018): 45-52.

[47] Kouziokas, Georgios N. "The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban environment." Transportation research procedia 24 (2017): 467-473.

[48] Araujo, Adelson, et al. "A predictive policing application to support patrol planning in smart cities." 2017 International smart cities conference (ISC2). IEEE, 2017.

[49] Gerber, Matthew S. "Predicting crime using Twitter and kernel density estimation." Decision Support Systems 61 (2014): 115-125.

[50] Vomfell, Lara, Wolfgang Karl Härdle, and Stefan Lessmann. "Improving crime count forecasts using Twitter and taxi data." Decision Support Systems 113 (2018): 73-85.

[51] Zhuang, Yong, et al. "Crime hot spot forecasting: A recurrent model with spatial and temporal information." 2017 IEEE International Conference on Big Knowledge (ICBK). IEEE, 2017.

[52] Cesario, Eugenio, Charlie Catlett, and

Domenico Talia. "Forecasting crimes using autoregressive models." 2016

[53] IEEE 14th Intl Conf on Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech). IEEE, 2016.

[54] Bogomolov, Andrey, et al. "Once upon a crime: towards crime prediction from demographics and mobile data." Proceedings of the 16th international conference on multimodal interaction. 2014.