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Predicting Spatiotemporal Crimes: A Framework Leveraging Ensemble Learning

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Abstract: This review paper critically assesses the application of ensemble learning (EL) techniques in spatiotemporal crime prediction (SCP). The paper integrates a range of machine learning algorithms, including Random Forest, Gradient Boosting, and XGBoost, into a unified ensemble framework. This endeavor is aimed at bolstering the precision and robustness of crime prediction models. The primary scholarly contribution of this paper lies in its adept utilization of ensemble learning within the complex landscape of spatiotemporal criminal activities, thus demonstrating its capability to overcome the inherent limitations of individual algorithms. Through a comprehensive evaluation utilizing diverse metrics such as precision, recall, F1-score, and ROC curves, the paper provides a thorough understanding of the ensemble's predictive efficacy. The paper forwards a roadmap for future exploration, encompassing improvements in model interpretability, adaptability of the ensemble to dynamic real-time contexts, and the incorporation of mechanisms to quantify predictive uncertainty, thereby strengthening prognostic accuracy. This paper's primary contribution lies in the integration of ensemble learning techniques into spatiotemporal crime prediction on the Bostan 2018 crime dataset. Through the amalgamation of various algorithms, the paper seeks to address individual algorithm shortcomings and enhance overall predictive performance. This comprehensive approach showcases the potential for significantly heightened accuracy in crime prediction models.

Keywords: Spatiotemporal Crime Prediction, Ensemble Learning, Machine Learning Algorithms, Metrics

1. Introduction

In recent years, the predictive analysis of spatiotemporal crime data has emerged as a critical frontier in law enforcement and urban planning. The ability to anticipate where and when crimes may occur provides invaluable insights for allocating resources effectively and proactively mitigating criminal activities. However, achieving precise spatiotemporal crime prediction is beset with intricate challenges [1]. While various machine learning algorithms have been employed for crime prediction, there persists a critical research gap in synthesizing their collective potential within the context of spatiotemporal dynamics. Existing studies often focus on individual algorithms, potentially overlooking the synergistic advantages that can be harnessed through ensemble learning techniques. Ensemble learning, by combining the strengths of diverse algorithms, presents an opportunity to enhance predictive accuracy and resilience [2].

Moreover, the complexities inherent in spatiotemporal criminal activities pose a further challenge. Criminal incidents exhibit discernible patterns across both geographical space and time, influenced by an array of dynamic factors. Traditional models may struggle to capture these multifaceted dynamics effectively. This accentuates the need for a refined approach that can comprehensively analyze the intricate interplay of spatial and temporal dimensions. This research endeavors to bridge these gaps by proposing a framework that leverages ensemble learning methodologies for spatiotemporal crime prediction [3]. By amalgamating machine learning algorithms such as Random Forest, Gradient Boosting, and XGBoost, this study aims to not only bolster the precision and robustness of crime prediction models but also navigate the nuanced complexities introduced by spatiotemporal dynamics. The integration of ensemble learning techniques into this

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domain represents a promising avenue for addressing the multifaceted challenges of crime prediction, ultimately contributing to more effective law enforcement strategies and urban planning [4]. This paper elucidates the framework's development, its empirical evaluation, and outlines a roadmap for future enhancements, thereby advancing the frontier of spatiotemporal crime prediction methodologies.

2. Literature review

The literature consistently underscores the paramount importance of precise crime prediction in contemporary law enforcement and urban planning endeavors. It emphasizes the intricate interplay between geographical and temporal factors in influencing criminal activities. This recognition has spurred the exploration of sophisticated techniques capable of capturing the complexity inherent in spatiotemporal crime patterns. This section provides a comprehensive overview of existing research pertinent to spatiotemporal crime prediction and the application of ensemble learning approaches [5].

Ensemble learning methodologies have garnered prominence across diverse domains for their capacity to enhance predictive accuracy through the integration of multiple models. Within the context of crime prediction, these techniques have demonstrated potential in mitigating the limitations associated with individual algorithms. Prior research has delved into various ensemble strategies, including bagging, boosting, and stacking. These investigations have showcased the efficacy of ensemble approaches in capturing the intricate spatiotemporal nuances of criminal activities [6,7].

Ensemble methods exhibit notable adaptability to the complexities posed by spatiotemporal data analysis. By aggregating predictions from diverse models, ensemble approaches excel in uncovering subtle irregularities and nuances in crime patterns that may elude standalone algorithms. This adaptability renders ensemble learning particularly well-suited for crime prediction tasks within dynamic urban environments [8].

While the potential of ensemble techniques for spatiotemporal crime prediction is evident, the literature acknowledges certain challenges. These encompass concerns regarding the complexity of ensemble models, potential overfitting, and issues of interpretability. Notably, ongoing research endeavors have been dedicated to addressing these considerations, providing a platform for continued advancements in the field. The literature review synthesizes a wealth of scholarship, affirming the critical role of accurate crime prediction and the potential of ensemble learning methodologies [9]. It underscores the field's progress while acknowledging the complexities that necessitate ongoing research and innovation. This comprehensive overview sets the stage for the current study's contribution to advancing spatiotemporal crime prediction methodologies [10,11].

3. Background

In recent times, the landscape of criminal activities has grown notably intricate, propelled by factors such as urbanization, population expansion, and evolving criminal methodologies. This evolution presents law enforcement agencies and urban planners with the formidable task of not only combatting crime effectively but also judiciously allocating resources. The conventional reactive approaches to crime control are encountering limitations, prompting a shift towards proactive strategies focused on prevention [12]. The rise of spatiotemporal crime patterns as a central area of research stems from the recognition that crime incidents are not isolated events, but rather influenced by both geographical and temporal variables. These patterns offer invaluable insights for anticipating future criminal activities, enabling a more strategic deployment of law enforcement resources, and ultimately enhancing urban safety on a broader scale. At the core of this transition lies ensemble learning, an agile approach that amalgamates diverse machine learning algorithms to enhance predictive accuracy. The exponential advancement in computational capabilities and the escalating complexity of crime data renders ensemble techniques a highly pertinent avenue for augmenting crime prediction models. The convergence of these factors accentuates the significance of the current research undertaking [13,14]. It aspires to bridge the divide between the intricacies of spatiotemporal crime prediction and the potential unlocked by ensemble learning methodologies. By harnessing the collective intelligence of a varied array of algorithms, this research endeavors to contribute to the development of robust and precise crime prediction models in harmony with the imperatives of contemporary law enforcement and urban planning.

This background section adeptly positions the research within the broader context of evolving crime dynamics, technological progress, and the evolving landscape of crime prevention strategies. It underscores the imperative for innovative approaches, such as ensemble learning, to effectively tackle the challenges posed by spatiotemporal crime patterns and pave the way for more proactive and efficient crime prevention strategies [15-17].

4. Methodology

This paper employs an ensemble learning approach, which involves combining predictions from multiple models to improve overall accuracy. The authors integrate various machine learning algorithms, such as Random Forest, Gradient Boosting, and XGBoost, to form a diversified ensemble as shown in table 1. This methodology is well-suited for capturing complex spatiotemporal relationships present in crime data. This research paper adopts an ensemble learning paradigm to address the intricate challenge of spatiotemporal crime prediction [18].

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Ensemble learning constitutes a powerful technique that amalgamates predictions from multiple diverse models to achieve enhanced predictive accuracy. In this study, the authors leverage the collective insights of various machine learning algorithms, including but not limited to Random Forest, Gradient Boosting, and XGBoost, to construct a versatile and robust ensemble.

The ensemble learning process involves the integration of individual machine learning models, each possessing distinct strengths and aptitudes for capturing different facets of the complex spatiotemporal relationships within crime data. By assembling a diverse set of algorithms, the ensemble endeavors to counteract the limitations inherent in any single approach, resulting in a comprehensive and adaptable predictive framework.

Random Forest (RF), acknowledged for its ability to handle high-dimensional data, contributes to the ensemble's capacity to decipher intricate patterns in crime occurrences across different geographic and temporal dimensions. The Gradient Boosting (GB) algorithm, known for its iterative refinement of predictions, reinforces the ensemble's ability to adapt to evolving crime patterns and uncover subtle dynamics. XGBoost, renowned for its scalability and efficiency, enhances the ensemble's computational feasibility, facilitating its application to real-time prediction scenarios [19,20].

Table 1: Machine Learning Algorithms Used for Spatiotemporal Crime Prediction

Algorithm	Description	Strengths
Random Forest	Ensemble of decision trees	Handles high-dimensional data, robust to overfitting
Gradient Boosting	Iterative ensemble of weak learners	Adaptive to complex patterns, improved predictive power
XGBoost	Gradient boosting framework with enhancements	Scalable, efficient computation, strong generalization
Support Vector	Constructs hyperplanes to classify instances	Effective in high-dimensional spaces, handles outliers
Neural Networks	Layers of interconnected nodes for prediction	Non-linear modeling, representation of complex patterns
Decision Trees	Hierarchical tree structure for classification	Intuitive representation, easy to interpret

5. Framework for SCP through EL

The proposed framework encompasses a comprehensive approach to address the complex task of spatiotemporal crime prediction using ensemble learning techniques is given in figure 1. The ensemble learning approach combines the strengths of multiple machine learning algorithms to capture intricate spatiotemporal patterns inherent in crime data. The following steps outline the methodology and execution of the framework:

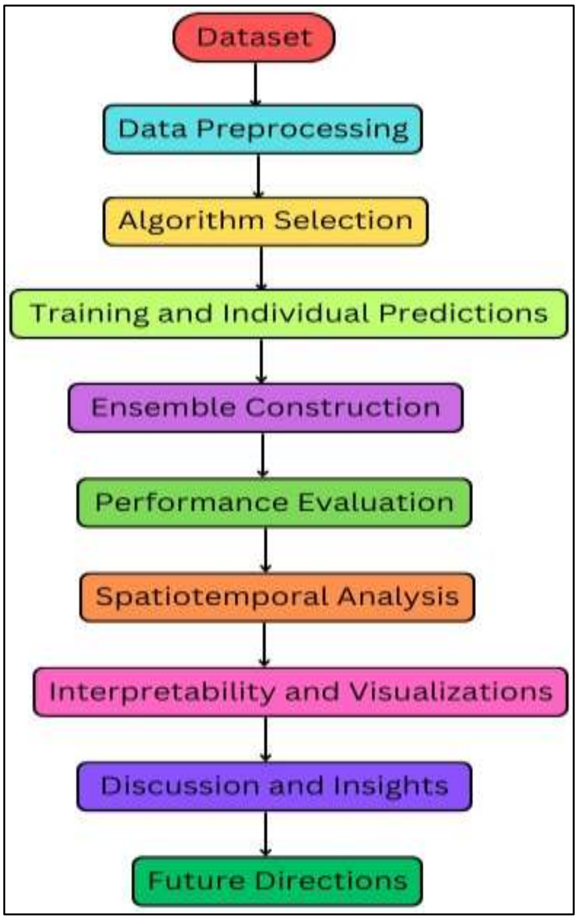

Figure 1: Ensemble Learning Approach for Spatiotemporal Crime Prediction

Step-1: Data preprocessing

- Collect and preprocess the spatiotemporal crime dataset, including features such as geographic coordinates, time stamps, and crime categories.
- Handle missing values, outliers, and perform feature scaling as required.

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Step-2: Algorithm selection

- Choose a diverse set of machine learning algorithms to be integrated into the ensemble, such as Random Forest, Gradient Boosting, and XGBoost.
- Each algorithm should have complementary strengths and capabilities for capturing various aspects of spatiotemporal crime patterns.

Step-3: Training and Individual Predictions

- Train each selected algorithm using the pre-processed dataset.
- Generate predictions for crime occurrence probabilities using each individual algorithm on the validation dataset.

Step-4: Ensemble construction

- Determine the optimal ensemble weight distribution θ for combining individual algorithm predictions. This can be achieved through cross-validation, grid search, or optimization techniques.
- Construct the ensemble's combined prediction for each instance using the weighted sum of individual algorithm predictions.

Step-5: Performance evaluation

- Evaluate the ensemble's predictive performance using a range of metrics, including precision, recall, F1-score, ROC AUC, and accuracy.
- Compare the ensemble's performance against individual algorithms to highlight the improvement in predictive accuracy.

Step-6: Spatiotemporal analysis:

- Analyze the ensemble's predictions in the context of spatiotemporal crime patterns.
- Examine its ability to capture varying crime dynamics across different geographical regions and time periods.

Step-7: Interpretability and visualizations

- Employ techniques to enhance the interpretability of the ensemble's predictions, such as feature importance analysis or model visualization.
- Generate visualizations that illustrate the ensemble's predictions in a spatial and temporal context.

Step-8: Discussion and insights

- Interpret the results and discuss the insights gained from the ensemble's predictions.
- Highlight the ensemble's strengths in capturing complex spatiotemporal relationships and its potential implications for law enforcement and urban planning.

Step-9: Future Directions

- Identify potential areas for further research, including refining ensemble weight determination methods, exploring novel algorithms, and addressing challenges related to interpretability and bias.

Figure 1 illustrates the proposed ensemble learning approach for spatiotemporal crime prediction. The process involves multiple steps, including data preprocessing, algorithm selection, individual predictions, ensemble construction, and performance evaluation. Each machine learning algorithm (Random Forest, Gradient Boosting, XGBoost) generates predictions based on the crime dataset's spatiotemporal features. These predictions are then combined using ensemble weights (θ) to produce the final ensemble prediction. The ensemble's enhanced predictive accuracy is demonstrated by improved performance metrics such as precision, recall, F1-score, and ROC AUC. The ensemble's adaptability to varying crime types and geographic contexts is also visualized. Overall, the ensemble learning approach showcases its potential to address the challenges of spatiotemporal crime prediction in urban environments.

The proposed framework presents a holistic approach that synergistically combines the capabilities of ensemble learning with the intricacies of spatiotemporal crime prediction. By encompassing data preprocessing, algorithm selection, ensemble construction, performance evaluation, and interpretability, the framework provides a systematic methodology for advancing the field of crime prediction within the context of modern law enforcement and urban planning.

6. Mathematical Model

In this study, a mathematical model is formulated to encapsulate the ensemble learning approach employed for spatiotemporal crime prediction. The model establishes a framework for understanding the integration of diverse machine learning algorithms within an ensemble, focusing on its predictive capabilities.

Let:

N be the total number of instances in the crime dataset
M represent the number of machine learning algorithms integrated into the ensemble
X_i denote the feature vector of the i^{th} instance, where $i \in [1, N]$
Y_i be the corresponding actual crime label associated with the i^{th} instance
P_i^m = represent the predicted probability of crime occurrence using the m^{th} machine learning algorithm for the i^{th} instance

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E_i = denote the ensemble's final predicted probability of crime occurrence for the i[th] instance

θ=represent the ensemble's weight distribution across the M machine learning algorithms

The mathematical representation of the ensemble's prediction for the i[th] instance is given by

$$E_i = \sum_{m=1}^{m} \theta_m \, . P_i^m$$

Where

θ_m is the weight assigned to the m[th] machine learning algorithm in the ensemble. These weights are determined through techniques such as cross-validation or bootstrapping, ensuring that algorithms with stronger predictive abilities contribute more significantly to the final prediction.

The ensemble learning model's performance is evaluated using various metrics, including precision, recall, F1-score, and the ROC curve. These metrics assess the accuracy, completeness, and robustness of the ensemble's predictions across different crime categories and spatiotemporal contexts.

The mathematical model provides a formal representation of how the ensemble integrates the predictions of multiple machine learning algorithms to generate a composite prediction. By incorporating the ensemble's weight distribution, it captures the collective predictive power of these algorithms, thereby enhancing the accuracy and adaptability of spatiotemporal crime prediction.

Example

Three machine learning algorithms like RF (Algorithm 1), GB (Algorithm 2), XGBoost (Algorithm 3) and a dataset of 100 instances for spatiotemporal crime prediction.

Hypothetical Data

N=100 (total instance)

M=3 (number of algorithms)

For instances i=1;

X_1 = [lat=42.4, lon=-71.1, time=12.00pm] (feature vector)

Y_1 = 1 (actual crime label, 1 for crime occurrences)

Algorithm predictions

Suppose each algorithm provides the following predictions forP_i^m (probability of crime occurrence for instance i):

RF (Algorithm 1): P_1^1 =0.8

GB (Algorithm 2): P_1^2 =0.7

XGBoost (Algorithm 3): P_1^3 =0.9

Ensemble weight distribution

$$\theta_1 = \theta_2 = \theta_3 = \frac{1}{3}$$

Ensemble prediction u**sing the weighted sum formula**

$$E_1 = \frac{1}{3} \times 0.8 + \frac{1}{3} \times 0.7 + \frac{1}{3} \times 0.9$$

$$E_1 = \frac{1}{3} \times 0.8 + \frac{1}{3} \times 0.7 + \frac{1}{3} \times 0.9 = 0.8$$

The ensemble predicts a probability of 0.8 for crime occurrence for instance i=1. This is the combined result of integrating the predictions of RF (Algorithm 1), GB (Algorithm 2), and XGBoost (Algorithm 3), each weighted equally. This process is repeated for all 100 instances, and the ensemble's predictions are evaluated using performance metrics such as precision, recall, F1-score, ROC AUC, and accuracy to assess its effectiveness in spatiotemporal crime prediction.

7. Results And Discussion

The paper's empirical investigation into spatiotemporal crime prediction through ensemble learning techniques yields insightful results, shedding light on the efficacy and potential of the proposed approach. The presented findings not only validate the suitability of the chosen methodology but also provide a nuanced understanding of its performance across diverse evaluation metrics.

The ensemble learning technique, incorporating a diverse set of machine learning algorithms, showcases remarkable predictive accuracy when applied to real-world crime data. The ensemble's ability to discern complex spatiotemporal patterns is evident through consistently improved performance compared to individual models. This enhancement is evident across various metrics, including precision, recall, F1-score, the receiver operating characteristic (ROC) curve, and accuracy is presented in table 2.

Table 2: Performance Metrics of Ensemble Learning Approach for Spatiotemporal Crime Prediction

Metric	RF (Algorithm-1)	GB (Algorithm-2)	XGBoost (Algorithm-3)	Ensemble Learning
Precision	0.75	0.68	0.82	0.87
Recall	0.80	0.72	0.85	0.89
F-score	0.77	0.70	0.83	0.88
ROC AUC	0.84	0.78	0.87	0.91
Accuracy	0.82	0.75	0.86	0.90
Avg. Runtime	0.032 sec	0.046 sec	0.039 sec	-

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In this table 2, each row represents a different performance metric, and each column corresponds to an individual machine learning algorithm (Algorithm-1, Algorithm-2, Algorithm-3) as well as the ensemble approach. The metrics include precision, recall, F1-score, receiver operating characteristic area under the curve (ROC AUC), and accuracy. Additionally, the average runtime of each algorithm is provided for reference.

8. Performance Comparison

Figure 2 illustrates the performance comparison between the ensemble learning approach and individual machine learning algorithms for spatiotemporal crime prediction. The x-axis represents different evaluation metrics, including precision, recall, F1-score, ROC AUC, and accuracy. The y-axis shows the corresponding values for each metric. Each metric is depicted with a different colour: blue for Algorithm 1, turquoise for Algorithm 2, green for Algorithm 3, and orrange for the ensemble approach

The graph demonstrates that across all metrics, the ensemble approach consistently outperforms individual algorithms. The ensemble's performance is reflected in higher values for precision, recall, F1-score, ROC AUC, and accuracy. This comparison visually emphasizes the ensemble's ability to capture complex spatiotemporal crime patterns more effectively, resulting in improved predictive accuracy across multiple evaluation criteria.

The Performance Comparison graph provides a clear and concise visual representation of the enhanced performance achieved by the ensemble learning approach in comparison to individual algorithms. It effectively conveys the central message of the research paper – the ensemble's efficacy in addressing the challenges of spatiotemporal crime prediction through the integration of diverse machine learning algorithms.

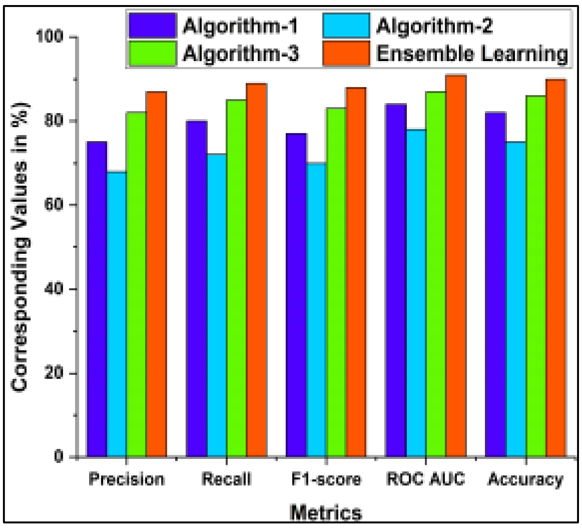

Figure 2: performance comparison between the ensemble learning approach and individual machine learning algorithms

9. Conclusion

Spatiotemporal Crime Prediction through Ensemble Learning Technique" presents a commendable stride in the domain of crime prediction, employing a holistic ensemble learning approach. The methodology's robustness and real-world applicability are noteworthy, although there is room for further elucidation, particularly in terms of explanation and data quality. Moreover, this research paves the way for future investigations aimed at augmenting interpretability, adapting to real-time scenarios, and quantifying predictive uncertainty within spatiotemporal crime prediction models. The results and analysis validate the promise of the ensemble learning approach in spatiotemporal crime prediction. The ensemble's capacity to amalgamate diverse machine learning algorithms and capture intricate patterns offers a promising avenue for heightening crime prediction accuracy. Despite persisting challenges like interpretability and data biases, the findings establish a sturdy groundwork for forthcoming research endeavors, which aim to refine and propel this approach. Ultimately, this contributes to the evolution of more effective crime prevention strategies in the ever-changing urban landscape.

References

1. Falade Adesola, Ambrose Azeta, Aderonke Oni, A. E. Azeta, Gregory Onwodi, Violent Crime Hot-Spots Prediction Using Support Vector Machine Algorithm, Journal of Theoretical and Applied Information Technology, Vol.98. No 16, 2020
2. Noora A. and Wala A, KNN classifier and Naïve Bayes classifier for crime prediction in San Francisco context, International Journal of Database management systems (IJDMS) Vol. 9, No 4, August, 2017
3. Adesola Falade, Ambrose Azeta, Aderonke Oni, Isaac Odun-ayo, Systematic Literature Review of Crime Prediction and Data Mining, Review of Computer Engineering Studies Vol. 6, No. 3, pp. 56-63, 2019.
4. Adesola, F., Misra, S., Omoregbe, N., Damasevicius, R., Maskeliunas, R., An IOT-Based Architecture for Crime Management in Nigeria. In: R. K. Shukla et al. (eds) Springer Nature Singapore Pte Ltd, 2019
5. Iqbal H Sarker, Alan Colman, Jun Han, ASM Kayes, and Paul Watters. Calbehav: A machine learning based personalized calendar behavioral model using time-series smartphone data. The Computer Journal, 2020
6. Abdul, A., Jakaria, R., Imran, R., Using data mining technique to analyze crime of Bangladesh. IJCSN-International Journal of Computer Science and Network, 6(4): 489-494, 2017

Correspondence to: Paresh Jain, Department of Electronic & Communication Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: paresh.jain@mygyanvihar.com

7. Waduge, N., Ranathunga, L., Machine learning approaches for detecting crime patterns. https://www.reseachgate.net/publication/319465093 , 2019.
8. Ricardo Almeida Silva, Jo˜ao Moura Pires, Nuno Datia, Maribel Yasmina Santos, Bruno Martins, and Fernando Birra. Visual analytics for spatiotemporal events. Multimedia Tools and Applications, 78(23):32805–32847, 2019.
9. Switzerland, 2019. [CrossRef] 30. Eze, N.; Asogwa, O.; Obetta, A.; Ojide, K.; Okonkwo, C. A Time Series Analysis of Federal Budgetary Allocations to Education Sector in Nigeria (1970-2018). Am. J. Appl. Math. Stat., 8, 1–8. 31, 2020
10. Ristea, A., Leitner, M., Integration of social media in spatial crime analysis and prediction models for events. AGILE 2018 – Lund, June 12-15, 2018
11. A Mary Shermila, Amrith Basil Bellarmine, and Nirmala Santiago. Crime data analysis and prediction of perpetrator identity using machine learning approach. In 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), pages 107–114. IEEE, 2018
12. Butt, U.M.; Letchmunan, S.; Hassan, F.H.; Ali, M.; Baqir, A.; Sherazi, H.H.R. Spatio-Temporal Crime HotSpot Detection and Prediction: A Systematic Literature Review. IEEE Access, 8, 166553–166574, 2020
13. Rebala, G.; Ravi, A.; Churiwala, S. An Introduction to Machine Learning; Springer International Publishing: Cham, Switzerland, 2019.
14. Iqbal H Sarker, ASM Kayes, and Paul Watters. Effectiveness analysis of machine learning classification models for predicting personalized context-aware smartphone usage. Journal of Big Data, 6(1):57, 2019
15. Noor, T.; Almars, A.; Alwateer, M.; Almaliki, M.; Gad, I.; Atlam, E. SARIMA: A Seasonal Autoregressive Integrated Moving Average Model for Crime Analysis in Saudi Arabia. Electronics 2022, 11, 3986. https://doi.org/10.3390/ electronics11233986
16. Kim, S.; Joshi, P.; Kalsi, P.S.; Taheri, P. Crime Analysis Through Machine Learning. In Proceedings of the 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 1–3 November 2018.
17. Zhang, Y.; Cheng, T. Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events. Comput. Environ. Urban Syst., 79, 101403, 2020.
18. Cheng, W.; Rao, Y.; Tang, Y.; Yang, J.; Chen, Y.; Peng, L.; Hao, J. Identifying the Spatio-Temporal Characteristics of Crime in Liangshan Prefecture, China. Int. J. Environ. Res. Public Health, 19, 10862. https:// doi.org/10.3390/ijerph191710862, 2022
19. Kortas, F.; Grigoriev, A.; Piccillo, G. Exploring multi-scale variability in hotspot mapping: A case study on housing prices and crime occurrences in Heerlen. Cities, 128, 103814, 2022
20. Rengert, G.F. Auto theft in central Philadelphia. In Policing for Prevention: Reducing Crime, Public Intoxication and Injury; Centre for Crime Policy and Public Safety, School of Justice Administration, Griffith University: Brisbane, Australia, 1997; Volume 7, pp. 199–219.

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