JOURNAL OF COMPUTING HORIZONS
Vol. 01, No. 01, 2026
DOI: 10.22610/JCH.V1I1.4989

RESEARCH ARTICLE | PEER REVIEWED

Explainable Crime Prediction Interpreting Machine Learning and Deep Learning Models for the Urban Safety Decision Making

Kinza Noor [1] *, Aiza Amin [1], Athar Rahim [1], Aqsa Akram [2]

[1] *Department of Artificial Intelligence, University of Management and Technology, Lahore (Sialkot Campus), Pakistan*

[2] *Department of Computer Science, University of Management and Technology, Lahore (Sialkot Campus), Pakistan*

* **Corresponding Author:** kinzaazeem967@gmail.com

ABSTRACT – Crime prediction has become an important research area that helps law enforcement agencies to make proactive decisions and improve public safety. In this study, a crime analytics framework is proposed that combines statistical forecasting and machine-learning-based classification techniques to analyze crime patterns and predict future crime. For forecasting, we use the ARIMA model, whereas for classification, XGBoost, Random Forest, Decision Tree, DNN, and Transformer are evaluated. ARIMA achieves ~29.06 RMSE, ~23.67 MAE, and ~0.4342 R^2, which shows its capability to model historical crime trends. In classification models, XGBoost achieved the best overall performance, with ~75.34% accuracy, ~0.8323 AUC, ~66.82% Precision, ~74.25% recall, and ~70.34% F1-score. Random Forest achieves ~80.25% recall, which is effective for identifying potential crime events. Results indicate that Machine learning and Deep learning techniques can improve crime prediction and can be useful for intelligent policing and smart city applications. For future work, to improve performance and interpretability, real-time data, spatiotemporal modeling, and Explainable AI (XAI) can be integrated.

Keywords: *Crime prediction; crime forecasting; machine learning; deep learning; ARIMA; XGBoost; random forest; transformer; smart cities; predictive analytics; explainable AI (XAI).*

I. INTRODUCTION

Retrieval: In today's world, crime prediction has become an important research area as urban populations, digital data, and smart city technologies grow rapidly. Traditional methods largely rely on manual investigation and statistical analysis, which are less effective with large datasets. Machine learning (ML) techniques help identify hidden patterns and relationships to improve predictive policing and public safety [1, 2]. Researchers also demonstrated that ML and deep learning improve the accuracy of crime forecasting by analyzing historical crime records, demographic factors, and spatiotemporal factors [3]. Earlier studies, such as self-exciting point process models, show the spatial and temporal patterns of crime [4], whereas Crime Pattern Theory explains the impact of environmental and social factors [5].

Although ML-based crime prediction has shown good performance, advanced models such as deep neural networks and ensemble learning algorithms are known as "black-box" systems because it is difficult to understand their decision-making process [6, 7]. In criminal justice, in sensitive domains, the lack of transparency can create ethical and legal concerns, because it is necessary for law enforcement agencies to understand on what basis the prediction was generated. For this reason, Explainable Artificial Intelligence (XAI) has become an important field that improves the interpretability, transparency, and trustworthiness of ML models [10, 11]. Explainable models help decision-makers understand which factors influence crime prediction and how the models generate predictions.

Different explainability techniques have been proposed to interpret ML models. For example, LIME explains individual predictions [8], while SHAP feature values provide important information [9]. These techniques improve user trust and accountability. According to researchers, interpretable and transparent AI systems are important in high-stakes areas such as healthcare, finance, and criminal justice [12]. Furthermore, explainable ML models are also used to improve the reliability and human understanding in real-world deployments [16]. The issues of fairness and accountability are present in predictive policing systems because biased datasets can produce discriminatory outcomes [13, 14, 15]. Bias in historical crime data has led to unfair targeting in some communities, undermining the reliability and ethical acceptance of predictive systems.

Along with this, the growth of big data and smart city infrastructures has increased the availability of real-time urban data. As a result, it becomes possible to develop frameworks for intelligent crime prediction [17, 18]. Data mining and knowledge discovery techniques play an important role in extracting meaningful information in large crime datasets [9]. Even now, the challenge of designing crime prediction systems that are not only accurate but also understandable, fair, and trustworthy remains.

The main purpose of this research is to develop an Explainable Crime Prediction system. This study will combine predictive accuracy with interpretability by applying XAI techniques, so that law enforcement and policymakers can better understand predictions and improve decision-making, accountability, transparency, and fairness.

II. RELATED WORK

The crime rate in recent years has increased due to rapid urbanization and population growth. Urban areas have factors such as high population density, economic inequality, and social issues that contribute to increased crime. That is why controlling crime and predicting future crime incidents are major challenges for law enforcement agencies and city authorities. To resolve this issue, researchers began implementing machine learning and explainable AI techniques to predict crime patterns in urban areas.

In the past, crime prediction was done through statistical methods. However, these methods were unreliable, as crime data is complex and does not follow simple patterns, and many factors are related to each other, like income, population, and education, which may cause uncertainty; to solve these issues, researchers started using Machine Learning & Deep Learning methods. Early machine learning models like KNN and SVM could make predictions, but they were not very strong. Later, more advanced models such as Random Forest performed much better, achieving up to 97% accuracy in forecasting violent crimes [1]. Furthermore, deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory LSTM) networks, were used to understand patterns in both time and location. These models were better at handling complex and real-world crime data [2].

More advanced models go a step further, such as Spatial-Temporal Meta-path guided Explainable Crime (STMEC), which not only showed important factors but also explained connections between different elements, such as relationships among people, locations, and social conditions, to understand crime patterns. An advanced model such as STMEC uses a special data structure called a Heterogeneous Information Network (HIN) [21]. Similarly, a deep neural network model was proposed for spatio-temporal crime event prediction. Real-world crime data was used, with crime type, location, and time-related features. The SMOTE technique was applied to handle data imbalance, and model hyperparameter tuning was performed. It was demonstrated that the proposed neural network model outperformed traditional machine learning models, improving the macro F1 score by ~6% [30]. By using meta-paths, these models provided human-readable logic that explains the factors contributing to crime risk, rather than just making predictions.

A machine learning and computer vision-based hybrid framework was proposed for crime forecasting. A geotagged crime records and surveillance imagery dataset was used, including spatial and temporal features. Random Forest and Convolutional Neural Network (CNN) models were applied to extract environmental and visual features. It was found that a hybrid machine learning and computer vision approach performed better, with higher accuracy, than traditional models. Also highlighted that lighting conditions, crowd density, and urban structure had a significant impact on crime occurrences [22].

Administrative crime data were used, along with demographic factors, population density, temporal features, and economic indicators. Researchers have compared the Neural network model with traditional statistical models such as linear regression and logistic regression. It was concluded that neural networks performed better at prediction and effectively captured complex non-linear relationships compared with traditional statistical models. Interpretability of Neural network models was limited, and models would become overfit [26]. A comparative analysis was conducted between machine learning techniques, deep learning techniques, and time-series models. For that research, a real-world crime dataset with temporal and spatial features was used. Researchers have applied machine learning models such as Decision Tree, Random Forest, and Support Vector Machine, along with deep learning models such as Multilayer Perceptron (MLP), and the time-series forecasting model ARIMA. Results demonstrated that deep learning-based MLP models achieved the highest performance. In contrast, the ARIMA model provided reasonable accuracy for time-series crime forecasting but was limited in its ability to capture complex patterns [2].

For crime prediction along with interpretability, an AIST (Attention-based Interpretable Spatio-Temporal) deep learning model was proposed. Real-world crime datasets for Chicago and New York City were used, including spatial regions, temporal patterns, and external features such as traffic flow and points of interest. An attention-based deep learning architecture is used to capture spatial and temporal dependencies. The proposed AIST model was compared with ARIMA, traditional ML, and DL baseline models. The study revealed that the AIST model achieved better performance, with MAE reduced by ~4% and MSE improved by ~7% [23]. Explainable AI is rapidly growing in the field of crime prediction. Explainable Artificial Intelligence concepts are discussed in detail, and balancing high-performance models alongside transparency and interpretability is important for adopting AI systems. These concepts were applied to crime prediction systems, where understanding the reasoning was significant for prediction [32].

However, the degree of interpretability varies across application domains. Interpretability in sensitive domains like Crime prediction requires technical requirements as well as accountability and fairness. An explainable deep neural network framework was proposed that uses prototype-based reasoning. By maintaining the predictive power of a deep learning framework, it generated understandable explanations. The xDNN approach would be implemented in crime prediction systems, where users are provided with explanations based on historical crime examples [34, 35]. In the Interpretable ML field, the Bayesian Rule sets framework was proposed, generating human-readable classification rules.

Rule-based explanation proved beneficial for law enforcement officials, as they used simple logical rules rather than complex mathematical outputs [33].

To analyze urban crime data, interpretable ML models for crime prediction and decision-making were proposed to identify feature importance. Results indicated that interpretable models helped law enforcement agencies analyze crime patterns and plan more effectively. It was also indicated that traditional black-box models were accurate, but interpretability was limited; on the other hand, interpretable models improve transparency [27]. The Degu city dataset was used, and multiple ML models were compared, including Random Forest, LightGBM, CatBoost & XGBoost, to analyze the relationship between urban environmental features and crime occurrence, and to propose an explainable artificial intelligence approach. XGBoost achieved ~89.7% accuracy. The SHAP explainability technique was used to identify important features, such as the visiting population, commercial areas, and the road network, that had a significant impact on crime occurrences. It was concluded that explainable AI models and crime prevention strategies are effective for urban safety [29].

For urban crime prediction, a Machine Learning-based approach was used to improve community safety. An urban crime dataset was used, and multiple machine learning models were applied to identify crime patterns. It was demonstrated that machine learning models helped to accurately predict crime hotspots and support law enforcement agencies for decision-making. However, machine model performance depends upon the availability and quality of the dataset [24, 25].

A Decision Tree-based J48 algorithm for crime prediction was implemented on historical crime data with features time, location, and crime type to identify crime patterns and predict future crime occurrences, achieving acceptable accuracy. It was concluded that decision tree models provided better support for planning and resource allocation to law enforcement agencies [28]. A systematic review on machine learning techniques for crime prediction was conducted. In the review, different machine learning models, including Random Forest, Decision Tree, Support Vector Machine, Neural Networks, and deep learning approaches, were analyzed. Results showed that Random Forest and Ensemble learning models achieved high accuracy, while deep learning models performed better for spatio-temporal crime prediction. It was also highlighted that the performance of crime prediction models highly depends on dataset quality and city-specific factors, and that data imbalance, limited datasets, and real-world deployment were limitations. It was concluded that explainable AI techniques, cross-city validation, and real-time datasets were essential for the reliability of crime prediction systems [31].

However, while supervised learning models have achieved high accuracy, there are still limitations: most models require high-quality data that is not publicly available, causing the field to lag behind other domains of social computing [22]. Another problem is that model accuracy varies by location and may not generalize across different landscapes or low-population areas where data is sparse [1, 20]. Machine learning, deep learning, and spatio-temporal approaches were used for crime prediction, showing better results in predicting crime patterns [1, 2, 3]. Interpretable models and explainable AI have been used to improve decision-making [23, 27, 29]. Urban metrics and environmental factors were used to enhance accuracy [20, 26]. Dataset dependency, high computational cost, limited interpretability, and limited real-time implementation were observed [24, 30, 31]. It is necessary to implement a model for reliable crime prediction in urban areas to enhance effectiveness.

III. METHODOLOGY

The purpose of this research is to predict crime occurrence and to use explainable machine learning techniques for urban safety decision making using the Chicago crime dataset. This study uses the Chicago crime dataset (2024-2026), which includes spatial and temporal information for different crime incidents. **Error! Reference source not found.** shows the methodology pipeline.

A. Dataset Collection

The dataset consists of different crime records with attributes such as District, Community area, Beat, Ward, Arrest Status, Domestic Status, Location Description, latitude, Longitude, and Year. Initially, relevant features were selected to extract meaningful information for crime prediction.

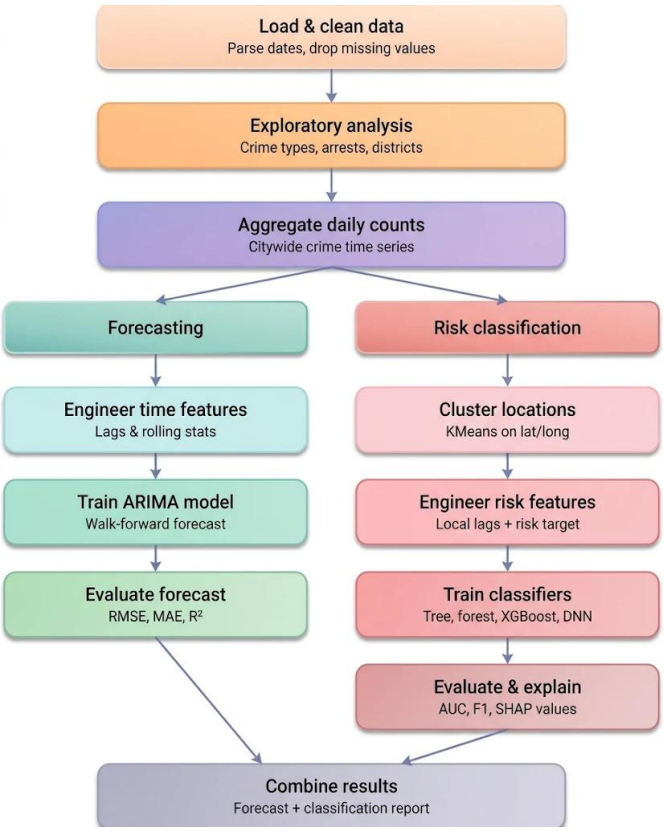


FIGURE 1: Forecasting and Risk Classification Pipeline

B. Data Preprocessing

Data preprocessing is the most important part for understanding data. Firstly, Missing values were identified and handled using appropriate techniques. Duplicate records were removed to enhance data quality. For converting categorical variables into numerical variables, label encoding was used. In particular, categorical columns such as District and Community areas were converted to an encoding format so that machine learning algorithms can process them. Numerical and categorical features were organized into a suitable format for model training. To evaluate generalization capability, data was divided into training and testing subsets.

C. Feature Selection

Location-based and crime-related features used as independent variables. These features include District, Community Area, Beat, Ward, Arrest, latitude, Longitude and Domestic. The target variable represents the classification objective for crime occurrence. To calculate the total number of crime incidents, aggregation is performed on the Date Only attribute. We get total counts from this feature. Moreover, to capture temporal patterns, calendar-based features such as Month, Day, Dayofweek, and IsWeekend are used. To represent the cyclic nature, sine and cosine transformations are applied. Here, the target variable Next-Day Crime count shows the total number of crimes the next day.

D. Crime Forecasting Model

ARIMA (Auto-Regressive Integrated Moving Average) model implemented for crime forecasting. ARIMA (2,1,2) configuration used, where p=2 autoregressive terms, d=1 differencing order, q=2 moving average terms. To maintain temporal order, data were divided into 80% for training and 20% for testing. RMSE, MAE, and R^2 were used to evaluate the forecasting model's performance. **Error! Reference source not found.** shows the ARIMA forecasting comparison.

E. Spatial Crime Clustering

K-means clustering was applied to latitude and Longitude coordinates to identify crime hotspots. 8 clusters were defined for that purpose. Each crime record is assigned to a geographical cluster using the Location_Cluster feature. These features represent spatial crime behavior.

F. Local Crime Risk

Daily crime counts were calculated for district, community area, and location clusters. Local lag features created to capture historical behaviors. Also, rolling statistics were calculated from the local rolling mean. Final analytical dataset created by global daily crime statistics and local area statistics.

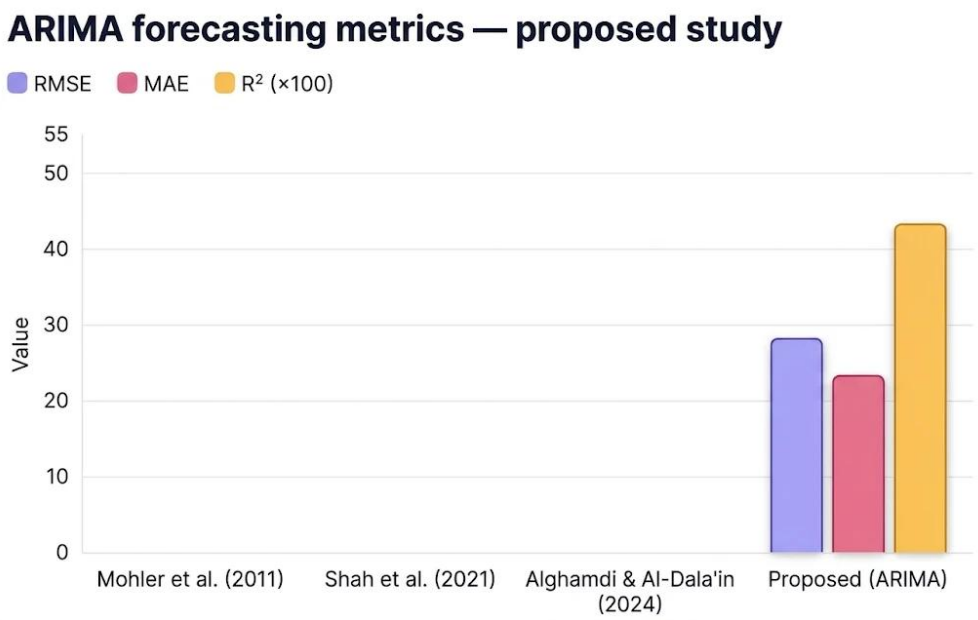


FIGURE 2: Comparison of ARIMA Forecasting Performance

G. Risk Classification Strategy

The next local count was calculated for each area, representing crime incidents for the next day. The median of the training dataset was used to create the threshold. Whereas, a binary target variable is created based on this threshold: 1 = High crime risk, 0 = low crime risk. This approach converted future crime into a binary classification problem.

H. Machine Learning Models

Multiple ML and DL models were implemented to compare performance in crime prediction. **Error! Reference source not found.** shows the classification models comparison.

1. Decision Tree Classifier

Decision tree algorithms were trained with controlled depth and optimized splitting parameters. This model provides crime prediction based on decision rules and offers interpretability.

2. Random Forest Classifier

Random Forest is an ensemble learning technique with multiple decision trees. This model reduces overfitting and improves prediction stability.

3. XGBoost Classifier

Extreme Gradient Boosting (XGBoost) is an advanced boosting framework. Hyperparameters such as learning rate, maximum depth, subsampling, and regularization coefficients are tuned to achieve optimal performance.

Model Performance Metrics Comparison

Model	AUC	Accuracy	Precision	Recall	F1-score
XGBoost	**0.83** ★	**0.75** ★	0.66	0.74	0.70
Random Forest	0.82	0.73	0.63	**0.80** ★	0.70
Transformer	0.82	0.73	0.63	0.79	0.70
DNN	0.82	0.74	0.65	0.75	0.70
Decision Tree	0.82	0.73	0.63	0.77	0.70

FIGURE 3: Classification Model Performance Comparison

I. Deep Learning Models

DL models like DNNs (deep neural networks) and Transformer-based models are used along with ML models.

1. Deep Neural Networks

The DNN architecture includes an input layer, a dense layer with 128 neurons, a ReLU activation layer, 30% dropout, another dense layer with 64 neurons, an activation layer, 20% dropout, and an output layer. A dropout layer is used to avoid overfitting. Adam optimizer and binary cross-entropy loss function are used to train the model.

2. Transformer Based Model

A tabular Transformer architecture was implemented with an input projection layer, transformer encoder layers, and a fully connected classification layer. The transformer model is used to understand complex relationships between tabular temporal-spatial features.

J. Model Evaluation

To evaluate classification models, the following metrics were used: Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC). The optimal classification threshold was determined using the Youden Index (TRP-FPR) approach. ROC Curve and confusion matrix were generated for each model.

K. Explainable Artificial Intelligence (XAI)

For explainability purposes, feature importance analysis was performed. The XGBoost feature importance approach was used to identify which features contributed most to the prediction. Through feature importance visualization, urban crime patterns were understood, providing actionable insights for decision-makers. **Error! Reference source not found.** shows the SHAP results.

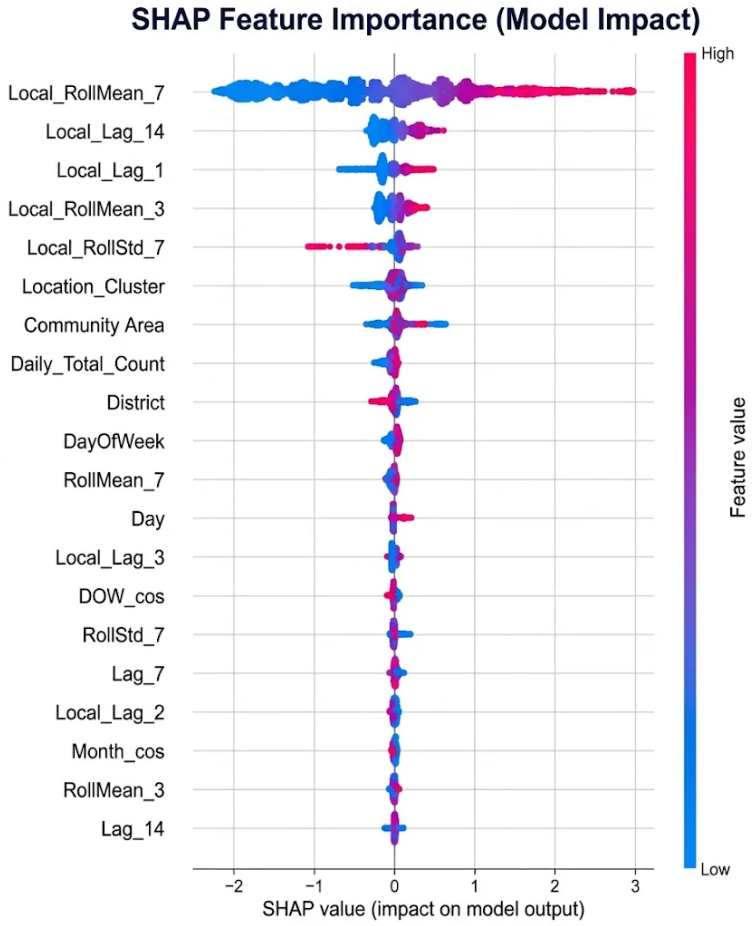


FIGURE 4: SHAP Impact on the Output by Input Features

Therefore, this methodology integrated crime forecasting with area-level crime risk prediction to support urban safety planning and resource allocation.

IV. RESULTS AND DISCUSSION

The proposed crime analytical framework evaluates both forecasting and classification. The ARIMA model is used for forecasting, while XGBoost, Random Forest, Transformer, DNN, and Decision Tree models are used for classification purposes. RMSE, MAE, R2, AUC, accuracy, precision, Recall, and F1 score metrics are used for performance evaluation. **Error! Reference source not found.** and **Error! Reference source not found.** show comparisons with the state of the art.

The ARIMA model achieved an RMSE of ~29.0626 and an MAE of ~23.6. R2 of ~0.4342 indicated that the model explained variance of ~43.4%. These results demonstrated that historical crime trends are useful for predicting future crime patterns. However, accuracy can be improved by accounting for the complexity of crime occurrence. Temporal models have been used for crime forecasting, but including spatial and social factors can enhance performance [4, 30].

Analysis of classification models shows satisfactory performance, but overall, XGBoost achieved higher results. XGBoost achieved the highest AUC of ~83% and an accuracy of ~75%. To reduce the number of cases missed, Random Forest is important, as it provides the highest Recall of ~80%. The Transformer model demonstrated competitive performance in capturing temporal and sequential relationships. DNN showed balanced performance and demonstrated its ability to identify complex patterns. Decision trees seem useful for interpretability but perform comparatively poorly. These findings showed that ensemble and deep learning models performed better than traditional approaches [1, 3, 23, 27].

V. CONCLUSION

In this research, forecasting and classification are two approaches for evaluating crime prediction. For the forecasting task, an ARIMA model is used, while the comparison of XGBoost, Random Forest, Transformer, DNN, and Decision Tree models is done for the classification task. The results showed that ARIMA can effectively capture historical crime trends and is useful for estimating future crime patterns.

Literature Review and Proposed Study Comparison

CLASSIFICATION STUDIES			
Study	**Task**	**Method / Technique**	**Performance**
Ahishakiye et al. (2017) [28]	Classification	Decision Tree (J48)	~70% accuracy
Safat et al. (2021) [3]	Classification	ML & DL models	70–75% accuracy
Jenga et al. (2023) [1]	Classification	Ensemble learning	AUC ~0.80
Rayhan & Hashem (2023) [23]	Classification	Attention-based DL	AUC ~0.82
Study	**FORECASTING STUDIES**		**Performance**
Mohler et al. (2011) [4]	Forecasting	Self-exciting point process	Moderate forecasting accuracy
Shah et al. (2021) [22]	Forecasting	ML-based forecasting	Improved crime trend prediction
Alghamdi & Al-Dala'in (2024) [30]	Forecasting	Spatio-temporal forecasting	Enhanced temporal accuracy
PROPOSED STUDY			
Study	**Task**	**Method / Technique**	**Performance**
Proposed study	Classification	XGBoost (classification)	★ AUC = 0.8323, 75.34% accuracy
	Forecasting	★ ARIMA (forecasting)	★ RMSE = 29.06, MAE = 23.67, R^2 = 0.4342

DL = deep learning • ML = machine learning • AUC = area under the ROC curve • RMSE = root mean square error
MAE = mean absolute error

FIGURE 5: Comparative Analysis of Existing and Proposed Methods

In classification models, XGBoost gave the best overall performance. Random Forest achieved the highest Recall which is important for public safety applications. Transformer and DNN also showed competitive performance and demonstrated the capability to identify complex crime patterns.



FIGURE 6: Accuracy and AUC Comparison of Classification Models

Overall, the results indicate that machine learning and deep learning techniques are more effective for crime prediction than traditional statistical approaches. This framework can support law enforcement agencies and smart city management systems in crime prevention and proactive decision-making.

VI. LIMITATIONS

Overall, like any research, this study also has some limitations:

- The dataset's size and quality were limited, which affected model performance.
- ARIMA considers only historical temporal trends and does not account for external factors.
- Spatial information and geographical crime hotspots are not applied in detail.
- Weather, economic indicators, and demographic factors are not included.
- For deep learning models, performance would have improved with larger datasets.
- Real-time crime data is not used.

REFERENCES

[1] K. Jenga, C. Catal, and G. Kar, "Machine learning in crime prediction," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 3, pp. 2887–2913, 2023.

[2] J. Yin, "Crime Prediction Methods Based on Machine Learning: A Survey," *Computers, Materials & Continua*, vol. 74, no. 2, 2023.

[3] W. Safat, S. Asghar, and S. A. Gillani, "Empirical analysis for crime prediction and forecasting using machine learning and deep learning techniques," *IEEE Access*, vol. 9, pp. 70080–70094, 2021.

[4] G. O. Mohler et al., "Self-exciting point process modeling of crime," *Journal of the American Statistical Association*, vol. 106, no. 493, pp. 100–108, 2011.

[5] P. J. Brantingham and P. L. Brantingham, "Crime Pattern Theory," *Environmental Criminology and Crime Analysis, Routledge*, 2008.

[6] F. Doshi-Velez and B. Kim, "Towards a rigorous science of interpretable machine learning," *arXiv preprint arXiv:1702.08608*, 2017.

[7] A. Adadi and M. Berrada, "Peeking inside the black-box: a survey on explainable artificial intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.

[8] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," *Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD)*, 2016.

[9] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," *Proc. Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017.

[10] A. B. Arrieta et al., "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Information Fusion*, vol. 58, pp. 82–115, 2020.

[11] R. Guidotti et al., "A survey of methods for explaining black box models," *ACM Computing Surveys*, vol. 51, no. 5, pp. 1–42, 2018.

[12] C. Rudin, "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," *Nature Machine Intelligence*, vol. 1, no. 5, pp. 206–215, 2019.

[13] V. Chiao, "Fairness, accountability and transparency: notes on algorithmic decision-making in criminal justice," *International Journal of Law in Context*, vol. 15, no. 2, pp. 126–139, 2019.

[14] R. Richardson, J. M. Schultz, and K. Crawford, "Dirty data, bad predictions: How civil rights violations impact police data, predictive policing systems, and justice," *NYU Law Review Online*, vol. 94, p. 15, 2019.

[15] K. Lum and W. Isaac, "To predict and serve?," *Significance*, vol. 13, no. 5, pp. 14–19, 2016.

[16] U. Bhatt et al., "Explainable machine learning in deployment," *Proc. ACM Conf. Fairness, Accountability, and Transparency (FAT)*, 2020.

[17] R. Kitchin, "The real-time city? Big data and smart urbanism," *GeoJournal*, vol. 79, no. 1, pp. 1–14, 2014.

[18] M. Batty et al., "Smart cities of the future," *The European Physical Journal Special Topics*, vol. 214, no. 1, pp. 481–518, 2012.

[19] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "From data mining to knowledge discovery in databases," *AI Magazine*, vol. 17, no. 3, pp. 37–37, 1996.

[20] L. G. A. Alves, H. V. Ribeiro, and F. A. Rodrigues, "Crime prediction through urban metrics and statistical learning," *Physica A*, vol. 505, pp. 435–443, 2018.

[21] Y. Sun, T. Chen, and H. Yin, "Spatial-temporal meta-path guided explainable crime prediction," *World Wide Web*, vol. 26, no. 4, pp. 2237–2263, 2023.

[22] N. Shah, N. Bhagat, and M. Shah, "Crime forecasting: a machine learning and computer vision approach to crime prediction and prevention," *Visual Computing for Industry, Biomedicine, and Art*, vol. 4, no. 1, p. 9, 2021.

[23] Y. Rayhan and T. Hashem, "AIST: An interpretable attention-based deep learning model for crime prediction," *ACM Transactions on Spatial Algorithms and Systems*, vol. 9, no. 2, pp. 1–31, 2023.

[24] S. Gupta and S. Sayer, "Machine learning for public good: Predicting urban crime patterns to enhance community safety," *arXiv preprint arXiv:2409.10838*, 2024.

[25] E. K. Zavadskas, R. Bausys, and I. Mazonaviciute, "Safety evaluation methodology of urban public parks by multi-criteria decision making," *Landscape and Urban Planning*, vol. 189, pp. 372–381, 2019.

[26] R. F. Reier Forradellas et al., "Applied machine learning in social sciences: neural networks and crime prediction," *Social Sciences*, vol. 10, no. 1, p. 4, 2020.

[27] X. Zhang et al., "Interpretable machine learning models for crime prediction," *Computers, Environment and Urban Systems*, vol. 94, p. 101789, 2022.

[28] E. Ahishakiye et al., "Crime prediction using decision tree (J48) classification algorithm," *International Journal of Computer and Information Technology*, vol. 6, no. 3, pp. 188–195, 2017.

[29] G. Kim et al., "Correlation analysis between urban environment features and crime occurrence based on explainable artificial intelligence techniques," *Journal of Asian Architecture and Building Engineering*, vol. 24, no. 6, pp. 5751–5770, 2025.

[30] J. Alghamdi and T. Al-Dala'in, "Towards spatio-temporal crime events prediction," *Multimedia Tools and Applications*, vol. 83, no. 7, pp. 18721–18737, 2024.

[31] O. Esan and B. Chimbo, "Systematic Literature Review on Crime Prediction using Machine Learning Techniques," *The Indonesian Journal of Computer Science*, vol. 14, no. 3, 2025.

[32] W. Samek, T. Wiegand, and K.-R. Müller, "Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models," *arXiv preprint arXiv:1708.08296*, 2017.

[33] T. Wang et al., "A Bayesian framework for learning rule sets for interpretable classification," *Journal of Machine Learning Research*, vol. 18, no. 70, pp. 1–37, 2017.

[34] Z. C. Lipton, "The mythos of model interpretability," *Queue*, vol. 16, no. 3, pp. 31–57, 2018.

[35] P. Angelov and E. Soares, "Towards explainable deep neural networks (xDNN)," *Neural Networks*, vol. 130, pp. 185–194, 2020.