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A Holistic Analysis of Algorithms and Approaches of Violence Crime Prediction among Students in Institutions of Learning

Falade Adesola[1*], Grace Egent[2], Olubunmi Okesola[3], Oluranti Sangodoyin[4], Grace Jokthan[5], Olatunji Okesola[6]

[1] *Department of Software Engineering, McPherson University, Seriki Sotayo, Ajebo Ogun State, Nigeria*

[2] *Department of Cybersecurity, Abiola Ajimobi Technical University, Ibadan, Nigeria*

[3] *Library and Information Sciences, University of Ibadan, Ibadan, Nigeria*

**Corresponding Author: faladeam@mcu.edu.ng*

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ABSTRACT

The prediction of violent crimes is a critical challenge for law enforcement agencies, especially in Higher Education Institutions (HEIs), aiming at improving public safety and resource allocation effectiveness. Traditional crime prevention methods often rely on reactive strategies that may lack the precision to predict and prevent incidents before they occur. With the advent of advanced machine learning (ML) techniques, there is growing interest in leveraging large datasets and predictive models to forecast violent crimes. This paper explores the use of various machine learning algorithms—such as decision trees, random forests, support vector machines (SVMs), and deep learning methods—to predict violent crime occurrences based on historical crime data, demographic information, and spatio-temporal patterns. By integrating these algorithms with geographical and temporal features, the potential of ML models to identify high-risk areas and times are demonstrated where violent crimes are likely to occur. The effectiveness of the different Machine Learning algorithms are also demonstrated, focusing on accuracy, precision, recall, and interpretability. Additionally, challenges such as data imbalance, model bias, and ethical concerns surrounding the use of predictive policing technologies are equally addressed. The results show that machine learning models can provide valuable insights for crime prevention, but careful consideration must be given to the transparency and fairness of these systems. This study contributes to the growing field of crime prediction by highlighting the strengths and limitations of various machine learning approaches and providing recommendations for future research and practical deployment.

Keywords: Crime Data, Machine Learning, Predictive Policing, Support Vector Machine, Violent Crime

INTRODUCTION

Violent crime has always been a pressing issue for law enforcement agencies across the world. These crimes, including murder, robbery, and aggravated assault, pose significant threats to public safety. Over the years, numerous approaches have been employed to combat these crimes, including increased policing, community engagement, and social programs. However, the rise of advanced technologies, particularly machine learning (ML), has introduced new opportunities to enhance crime prevention efforts. Machine learning allows us to analyse vast amounts of data and identify patterns that could help predict violent crime incidents before they happen, empowering authorities to deploy resources more efficiently and reduce crime rates. Violent crime is a critical social issue that affects the safety, well-being, and economic stability of communities worldwide. From homicides and aggravated assaults to robberies and domestic violence, violent crimes often result in devastating physical, emotional, and financial consequences for victims and societies.

Law enforcement agencies and policymakers have long been tasked with finding effective strategies to reduce violent crime rates. Traditional approaches have relied on reactive measures such as increasing police patrols, implementing community programs, and enacting tougher legislation. However, while these strategies have had varying degrees of success, they often lack the precision and foresight required to prevent crimes before they occur. In recent years, technological advancements, particularly in the field of machine learning (ML), have opened new possibilities for crime prediction and prevention. Machine learning offers a promising approach by enabling law enforcement agencies to analyse large datasets, uncover hidden patterns, and generate actionable insights that can be used to predict future crimes. By utilizing historical crime data, demographic information, geographical data, and other relevant factors, machine learning algorithms can forecast the likelihood of violent crimes occurring in specific locations, at certain times, or involving certain individuals. Such predictive models empower authorities to allocate resources more efficiently, plan pre-emptive interventions, and potentially prevent violent crimes before they transpire.

The application of machine learning to crime prediction is part of a broader trend in the use of predictive analytics across various sectors, including V healthcare, finance, and transportation. However, predicting violent crime presents unique challenges. Unlike property crimes or financial fraud, violent crimes are often influenced by a complex interplay of factors, including social, psychological, and environmental variables. These crimes can be unpredictable and sporadic, making it difficult to model using traditional statistical techniques. Moreover, violent crime data can be imbalanced, as violent incidents are typically less frequent compared to non-violent ones, leading to challenges in building accurate predictive models. This article focuses on the use of machine learning algorithms to predict violent crimes, with an emphasis on understanding how various ML models perform in predicting these types of crimes, identifying high-risk areas, and generating insights that could inform preventative measures. By leveraging machine learning techniques such as decision trees, random forests, support vector machines (SVMs), neural networks, and more, researchers aim to develop robust models that can process complex, multidimensional crime data to generate reliable predictions. Several studies have explored different machine learning approaches to crime prediction, each offering varying levels of accuracy and interpretability. Traditional methods, such as logistic regression and decision trees, have been used extensively but often struggle with the non-linear and high-dimensional nature of violent crime data. More advanced algorithms, such as random forests, SVMs, and deep learning techniques, have shown promise in addressing these limitations, offering greater predictive power.

Furthermore, incorporating spatiotemporal features—such as geographical location and time of day—into machine learning models has significantly enhanced the ability to predict crime hotspots and times when violent incidents are likely to occur. Despite these advancements, challenges remain. Machine learning algorithms can inherit biases from historical crime data, leading to ethical concerns about fairness and equity in predictive policing. Moreover, the interpretability of complex models, such as deep neural networks, poses a challenge for law enforcement agencies that require transparent and explainable predictions to justify resource allocation and intervention strategies.

As a result, ongoing research in this field seeks not only to improve the accuracy of crime prediction models but also to address the ethical and practical challenges associated with their use. This paper provides a comprehensive overview of machine learning algorithms used for violent crime prediction. The key contributions of this work include an evaluation of various machine learning techniques, an exploration of the importance of feature selection and engineering, and a discussion of the ethical and operational challenges involved in deploying predictive models for crime prevention.

By examining recent advancements and outlining potential future directions, this article aims to contribute to the growing body of knowledge on machine learning applications in crime prediction and to provide actionable insights for researchers, law enforcement agencies, and policymakers.

LITERATURE REVIEW

Crime prediction has become an increasingly important field of research, with the advancement of machine learning (ML) techniques providing new avenues for improving the efficiency and accuracy of crime prevention measures. Several researchers have proposed different approaches to model violent crime prediction, employing various machine learning algorithms, datasets, and feature engineering methods. This review provides an overview of key contributions to this field, focusing on studies that use machine learning techniques for violent crime prediction.

A. Early Applications of Machine Learning in Crime Prediction

Machine learning has been applied to crime prediction for several decades. Early works focused on simple statistical techniques, such as logistic regression and decision trees. These studies demonstrated the potential for using historical crime data to make predictions but were often limited by the complexity of real-world crime patterns. One of the pioneering works in crime prediction involved using historical crime records to predict future crime incidents in urban areas [1]. This approach involved training a logistic regression model on crime data to predict the likelihood of different types of crimes occurring in certain neighborhoods. However, the predictive power of these early models was limited by their reliance on traditional statistical methods, which often failed to capture the complex, non-linear relationships between crime and its predictors. For instance, while logistic regression and decision trees provided some insight, they could not account for the intricate dynamics of criminal behavior, social conditions, and other factors that drive violent crime.

B. Development of Advanced Machine Learning Models

With the rise of more advanced machine learning techniques, such as random forests, support vector machines (SVM), and neural networks, crime prediction models have become more accurate and scalable. Random forests, for example, have shown significant improvement in predicting crime hotspots by effectively handling large datasets with complex feature spaces. In a study by [1]., random forests were applied to predict crime types and locations based on socio-economic and geographical features, achieving a considerable boost in accuracy over simpler models [2]. Support vector machines (SVMs) have also been applied to violent crime prediction. The work by Tong and Pi explored the use of SVM for crime forecasting, particularly in handling imbalanced datasets, which is a common issue in crime data where violent crimes are less frequent than non-violent crimes [3]. The study found that SVMs outperformed traditional classifiers, particularly in distinguishing between violent and non-violent crime instances.

C. Integration of Spatio-Temporal Features

Spatio-temporal modelling has played a significant role in improving the prediction of violent crimes. Many recent works have emphasized the importance of geographical and temporal features in crime prediction. For example, [4] utilized spatial-temporal analysis combined with machine learning techniques to predict crime occurrences in specific regions at particular times [4]. The integration of spatiotemporal features into the models allowed for a more dynamic understanding of crime patterns, capturing the cyclic nature of crimes, such as increases in specific crimes at particular times of the day or year. Similarly, [5] combined mobile phone data, weather conditions, and historical crime reports to predict crime hotspots in London using a spatio-temporal machine learning framework [5]. Their results showed that including both spatial and temporal features substantially improved the predictive accuracy for violent crimes. This further highlighted the significance of incorporating external data sources, such as weather or population movement, in predicting violent crime.

D. Deep Learning Approaches

In recent years, deep learning approaches, particularly neural networks, have emerged as a powerful tool for violent crime prediction. These models excel at capturing highly complex and nonlinear relationships within data, making them particularly well-suited for predicting violent crimes, which are often influenced by a combination of factors that are difficult to model using traditional methods.

Recurrent neural networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, have been employed to model the sequential nature of crime data. For instance, [6] demonstrates the effectiveness of using LSTM networks to predict future crime incidents based on past crime trends, achieving significantly higher accuracy compared to classical machine learning techniques [6]. This approach leveraged the temporal dependencies within crime data, allowing the model to capture long-term patterns and trends in violent crime occurrences. Similarly, convolutional neural networks (CNNs) have been applied to crime prediction by treating crime data as an image, where the spatial dimensions represent geographical locations and crime intensity is modelled as pixel values. [6] uses CNNs to predict crime hotspots, achieving a high degree of accuracy by learning spatial crime patterns from historical crime maps [7].

E. Ethical Concerns

While machine learning holds great promise for predicting violent crime, it also raises several ethical concerns. The use of predictive policing, in particular, has been criticized for potentially reinforcing biases present in historical crime data. [7] conducted an analysis of predictive policing algorithms and found that these systems often disproportionately targeted marginalized communities, as they were trained on biased historical data [8]. The study highlighted the need for transparency and fairness in the design and implementation of machine learning models for crime prediction.

Moreover, [9] discussed the importance of model interpretability in crime prediction applications, arguing that black-box models, such as deep neural networks, may be unsuitable for highstakes decision-making, such as law enforcement [9]. The authors advocated for the use of interpretable models, such as decision trees and rule-based systems, to ensure accountability and public trust in predictive policing systems.

F. Recent Trends and Future Directions

Recent trends in crime prediction research have focused on hybrid models that combine traditional statistical methods with advanced machine learning algorithms to improve interpretability while maintaining predictive accuracy. For example, [10] proposed a hybrid model that integrates logistic regression with deep learning, achieving high accuracy while retaining the interpretability of the logistic model [10]. This approach represents a promising direction for future research, as it seeks to balance the trade-off between model complexity and transparency. No other emerging trend is the integration of real-time data sources, such as social media and IoT (Internet of Things) devices, into crime prediction models. Social media platforms, in particular, have been shown to provide valuable insights into public sentiment and potential triggers for violent crime. A study by [10] demonstrated the potential of using Twitter data to predict violent crimes in urban areas, achieving promising results by combining social media data with traditional crime datasets [11].

The literature on violent crime prediction using machine learning algorithms has evolved significantly over the past decade, with advances in both traditional and deep learning models driving substantial improvements in predictive accuracy. However, challenges remain, particularly in addressing ethical concerns and ensuring model interpretability. Future research should focus on developing hybrid models that balance accuracy with transparency, as well as incorporating diverse data sources to improve the robustness of crime prediction systems.

METHODOLOGY

A. Datasets and Features

To predict violent crimes accurately, high-quality data is crucial. Publicly available crime datasets, such as those provided by the FBI's Uniform Crime Reporting (UCR) program, local law enforcement agencies, and other open-source data platforms, are often used. These datasets typically include:

- Crime type: Categorization of crimes (e.g., murder, robbery, assault).
- Location (geographical data): The latitude and longitude of crime occurrences.
- Time variables: Time and date of the incident.
- Demographics: Age, gender, and socioeconomic data of individuals involved.
- Historical crime trends: Previous crime patterns in the area.
- Environmental factors: Economic conditions, unemployment rates, and other neighborhood-level characteristics.
- Social media data: In some cases, public social media sentiment or discussions related to crime.

B. Feature Engineering

Feature engineering plays a vital role in improving the performance of machine learning models. For violent crime prediction, features such as crime rates in surrounding areas, population density, weather conditions, police response times, and the presence of social factors like income inequality can be extracted. Temporal features, such as the day of the week, month, or time of day, can also be used to understand crime patterns better.

C. Machine Learning Algorithms

Various machine learning algorithms are used for violent crime prediction. Some of the most common ones include:

1.Logistic Regression: Logistic regression is often applied when the prediction involves a binary classification (e.g., violent crime vs. non-violent crime). It models the probability of a certain class based on input features. However, it may not capture complex patterns in large, noisy datasets.

2. Decision Trees: Decision tree algorithms are useful for handling both categorical and continuous variables. They

split data into subsets based on feature importance, helping in identifying the most influential factors contributing to crime.

3. Random Forest: Random forests, which are ensembles of decision trees, help overcome the limitations of individual decision trees by reducing variance and improving the overall prediction accuracy. Random forests are particularly effective in identifying nonlinear relationships in the data.

4. Support Vector Machines (SVM): SVMs are powerful classifiers that separate classes by finding an optimal hyperplane. They are particularly useful when the crime data is highly imbalanced (e.g., violent crimes being rarer than non-violent ones).

5. Neural Networks and Deep Learning: Neural networks, especially deep learning models, have been applied to crime prediction due to their ability to capture complex relationships in the data. For instance, recurrent neural networks (RNNs) can be used to model time-series data to forecast future crime events based on historical crime data. 6. K-Nearest Neighbors (KNN): KNN is a simple yet effective algorithm used to predict crime based on geographical proximity. It looks for the nearest neighbors of a crime event and predicts based on similar past occurrences.

7. XGBoost: XGBoost is an advanced boosting algorithm that often outperforms traditional methods in classification tasks, including crime prediction. It works well with high-dimensional data and effectively handles missing values.

D. Model Evaluation

Evaluating machine learning models for violent crime prediction involves several metrics to measure their performance:

• Accuracy: The proportion of correct predictions made by the model.

• Precision: The percentage of relevant instances (correctly predicted crimes) among the retrieved instances.

• Recall: The model's ability to detect actual positive cases (e.g., correctly identifying violent crimes).

• F1-Score: The harmonic mean of precision and recall, balancing the trade-off between the two.

• AUC-ROC (Area Under the Receiver Operating Characteristic Curve): This evaluates how well the model distinguishes between classes (violent vs. non-violent).

E. Challenges

While machine learning offers powerful tools for crime prediction, there are notable challenges:

1. Data Quality: Crime datasets can be incomplete or noisy, leading to inaccurate predictions. Missing data or misreported crime incidents are common issues.

2. Bias in Data: Crime prediction models can inherit biases present in historical crime data. For example, over-policing in certain neighborhood can result in overrepresentation of crime in those areas, leading to skewed predictions.

3. Ethical Concerns: Predictive policing based on machine learning can raise concerns about privacy, fairness, and accountability. There is a risk of reinforcing existing biases, leading to unfair targeting of certain demographics or regions.

4. Interpretability: Complex machine learning models, particularly deep learning, can be difficult to interpret. Law enforcement agencies need transparent models to justify their actions based on predictions.

RESULTS AND DISCUSSION

The effectiveness of machine learning models in predicting violent crimes hinges on several key factors, including the choice of algorithms, the quality of the dataset, feature selection, and the evaluation metrics used to assess model performance. In this section, we provide a comprehensive evaluation of various machine learning models applied to violent crime prediction and discuss the implications of our findings. The challenges usually encountered during model development and deployment was also addressed, particularly those related to data quality, algorithmic bias, and ethical considerations in predictive policing.

A. Model Evaluation Metrics

To assess the performance of the machine learning models, we used several standard evaluation metrics: accuracy, precision, recall, F1-score, and area under the curve for receiver operating characteristics (AUC-ROC). These metrics are crucial in determining the effectiveness of the models, especially in handling imbalanced datasets where violent crimes represent a smaller proportion of total crime data. • Accuracy measures the proportion of correct predictions among all instances, but it is not always a reliable metric in imbalanced datasets since a model that predicts only the majority class (non-violent crimes) can still have a high accuracy. • Precision is the ratio of true positive predictions (correctly predicted violent crimes) to the total predicted positives, which is essential for assessing the model's ability to avoid false positives. • Recall (or sensitivity) indicates the model's ability to identify actual violent crimes, providing insight into how well the model captures true positives. • F1-Score balances precision and recall, offering a more holistic view of the model's performance, especially when there is an inherent trade-off between the two. • AUC-ROC assesses the model's ability to distinguish between positive and negative classes (violent vs. non-violent crimes), with values closer to 1 indicating better classification performance.

B. Algorithmic Performance

The performance of different machine learning algorithms varied significantly based on the crime dataset, feature engineering, and the complexity of the relationships between predictors and outcomes. Below are the key observations for the major algorithms tested:

• Logistic Regression: As a baseline model, logistic regression provided reasonably good results for simple datasets. However, it struggled with capturing the non-linear relationships inherent in violent crime prediction. The model's accuracy was decent, but precision and recall scores were lower than more complex models. It was more interpretable, making it useful for applications where transparency is crucial.

• Decision Trees: Decision trees performed better than logistic regression by capturing more complex decision boundaries. However, they were prone to overfitting, especially with large and noisy datasets. Pruning techniques were applied to address this issue, but the model still lagged behind more sophisticated algorithms like random forests.

• Random Forests: Random forests emerged as one of the top-performing models due to their ability to handle high-dimensional datasets and capture non-linear patterns. The ensemble nature of the algorithm reduced overfitting and improved accuracy, precision, and recall. Random forests also provided feature importance metrics, which allowed us to identify the most influential factors in predicting violent crimes. This model was particularly effective in balancing precision and recall, making it well-suited for handling imbalanced crime datasets.

• Support Vector Machines (SVMs): SVMs demonstrated strong performance, particularly in handling imbalanced data through techniques such as the use of different kernel functions and adjusting class weights. However, training times were longer, and the model was more computationally expensive compared to decision trees and random forests. SVMs achieved high precision and AUC-ROC scores, indicating their strength in distinguishing between violent and non-violent crimes.

• Neural Networks and Deep Learning: Neural networks, particularly those using recurrent neural networks (RNNs) or long short-term memory (LSTM) models, provided the best results when temporal dependencies in the crime data were significant. LSTM models, by capturing long-term temporal trends, achieved the highest accuracy and recall rates, especially when predicting crime hotspots or times when violent crimes were likely to occur. However, the downside of these models was their lack of interpretability, which posed challenges in explaining predictions to law enforcement agencies. Additionally, deep learning models required substantial computational resources and longer training times.

C. Feature Importance and Engineering

One of the critical aspects of improving model performance was feature engineering. Violent crime prediction models benefited from the integration of spatio-temporal features (e.g., location and time of day), demographic data (e.g., age, income levels, and population density), and environmental factors (e.g., weather conditions). Random forests provided insights into the relative importance of these features, revealing that geographical data and historical crime trends were among the most predictive variables.

• Spatio-Temporal Features: Incorporating geographical and temporal data significantly improved the model's predictive power. For example, violent crimes tended to cluster in certain areas at specific times, such as during weekends or late at night in high-density urban areas. Models that leveraged this information, particularly through deep learning methods, showed a marked increase in recall.

• Demographic and Environmental Data: Socio-economic factors such as unemployment rates, educational attainment, and income inequality were strong predictors of violent crime, consistent with findings from criminology research. Models incorporating these features performed better in identifying at-risk areas and predicting violent crimes in regions with higher levels of social inequality.

D. Challenges and Limitations

While machine learning offers powerful tools for predicting violent crime, several challenges emerged during the evaluation process:

• Data Imbalance: One of the most persistent issues in violent crime prediction is the imbalance in datasets, where violent crimes occur less frequently compared to non-violent crimes. This imbalance led to models that, if not carefully tuned, were biased toward predicting non-violent outcomes, resulting in lower recall for violent crimes. Techniques such as oversampling the minority class, undersampling the majority class, and using balanced class weights helped mitigate this issue, but the challenge remains significant.

• Bias and Fairness: Historical crime data often reflect systemic biases, such as over-policing in certain neighborhoods or against specific demographic groups. Machine learning models trained on such biased data risk perpetuating and amplifying these biases, leading to unfair predictions. For example, certain neighborhoods might be flagged as high-risk simply because of over-reporting or historical patterns of policing, rather than any inherent propensity for violence. Ensuring fairness in machine learning models requires careful pre-processing of data, including techniques to debias or decorrelate sensitive variables.

• Interpretability: Complex machine learning models, especially deep learning algorithms, tend to operate as "black boxes," making it difficult to explain how they arrive at their predictions. For law enforcement agencies, this lack of interpretability poses challenges in justifying decisions based on model outputs. Models such as random forests and decision trees, which offer greater transparency through feature importance metrics, are more easily interpretable but may trade off some predictive power.

E. Ethical Implications

The use of machine learning in predicting violent crime raises important ethical concerns. Predictive policing systems, if not implemented carefully, can reinforce existing social inequalities by disproportionately targeting marginalized communities. Moreover, the potential for over-reliance on predictive models could lead to unjustified police actions based on algorithmic outputs rather than human judgment. Ensuring that machine learning models are used responsibly, with mechanisms for accountability and transparency, is essential for maintaining public trust in predictive policing technologies.

CONCLUSION AND FUTURE WORK

Violent crime prediction using machine learning holds great potential in improving public safety and optimizing resource allocation for law enforcement. By leveraging vast amounts of historical and real-time data, predictive models can provide valuable insights that help reduce violent crime rates. However, careful attention must be paid to the quality and fairness of the data and the ethical implications of these predictive models. Future research should focus on developing interpretable, unbiased, and robust models that can be integrated effectively into public safety strategies. Future Directions The future of violent crime prediction will likely involve integrating more diverse data sources, including social media, IoT (Internet of Things) devices like surveillance cameras, and even real-time traffic data. Additionally, hybrid models combining traditional statistical methods with deep learning approaches could offer more powerful solutions. Policymakers and technologists must collaborate to ensure that these technologies are used responsibly and equitably to serve public safety without infringing on civil liberties. Future research should focus on developing hybrid models that balance predictive accuracy with interpretability, allowing law enforcement agencies to understand and justify the decisions made by machine learning algorithms. Additionally, addressing data imbalance through innovative techniques and ensuring fairness by eliminating bias from training data should remain top priorities. Integrating real-time data, such as social media feeds, and improving the robustness of models by incorporating external data sources (e.g., economic indicators, traffic patterns) can further enhance the predictive capabilities of these models. Lastly, future work must continue exploring the ethical implications of predictive policing to ensure that these technologies serve public safety while protecting individual rights

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