Fast Prediction of Criminal Suspects:
An Ensemble Learning Approach

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Abstract- This research paper proposes a fast prediction system for criminal suspects using ensemble learning algorithms. The system aims to forecast criminals efficiently by analyzing diverse crime dataset properties, including geographical location, crime types, historical crime rates, and socio-economic factors. The system utilizes Python, MySQL, and Flask for programming, data storage, and web application development. The algorithms implemented include 'Logistic Regression, Linear Regression, Random Forest, Decision Tree, Extra trees classifier, and k-Nearest Neighbors (kNN)' for predicting criminal activities. The feasibility study encompasses economic, technical, and social considerations, ensuring alignment with financial, technical, and societal parameters.

The proposed system effectively combines multiple classifiers, leading to improved prediction performance in identifying potential criminal suspects. The ensemble learning approach contributes to more effective criminal activity prevention plans and resource allocation. The system's high accuracy and potential to improve law enforcement decision-making make it a valuable tool for modern policing. However, ethical considerations and societal impact must be addressed, ensuring that the system respects civil liberties and privacy rights.

Keywords: Prediction, Criminal Suspects, Ensemble Learning Algorithms, Crime Types, Historical Crime Rates, Socio-economic Factors, 'Logistic Regression', 'Linear Regression', 'Random Forest', 'Decision Tree', 'k-Nearest Neighbors'.

I. INTRODUCTION

The fast prediction of criminal suspects is a critical area of research in the broad area of law enforcement and criminal justice. The primary goal of this project is to develop a system that can efficiently forecast potential criminal suspects by analyzing diverse crime datasets, including geographical location, crime types, historical crime rates, and socio-economic factors. The system employs a unique set of classifier algorithms, such as Random Forest, k Neighbors, Logistic Regression, Linear Regression, and Decision Tree, to suggest potential suspects. This predictive module enables swift identification of suspects, contributing to more effective and powerful criminal activity prevention strategies and resource allocation.

The project follows a systematic approach, involving planning, development, testing, and deployment phases. The planning phase includes identifying stakeholders, defining project scope, conducting a feasibility study, establishing requirements, and creating a project plan. The development phase consists of designing architecture, data collections and preprocessing, algorithm development, software development, and integration and testing. The testing phase comprises unit-testing, integration-testing, system-testing, and user acceptance-testing (UAT). The deployment phase covers deployment planning, installation, training and

documentation, monitoring and support, updates and enhancements, and data management.

The algorithms implemented in this paper include 'Logistic Regression, Linear Regression, Random Forest, Decision Tree, and k-Nearest Neighbors (k-NN)'. Logistic Regression is a statistical method commonly used in ML for binary classification problems, and it can be applied to predict criminal activities according to crime dataset. In the area of criminal prediction, the algo aims to model the relationship in between a collection of independent variables (features extracted from the crime dataset) and the likelihood of a criminal event occurring (binary outcome – crime or no crime).

This idea to train and test models to ensure highest accuracy and precision has led to the implementation of multiple algorithms and compare them which might come in handy, these models are as follows:

Linear Regression

Linear Regression is a fundamental statistical method used for predictive analysis, particularly in situations where the relationship between the dependent variable (the outcome or target) and one or more independent variables (predictors) is assumed to be linear.

How it Works:
In linear regression, the goal is to find the best-fitting line (also called the regression line) through the data points, which minimizes the error between the actual data points and the predicted values. This line can be represented by the following equation: $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$.
Where:
- Y is the dependent variable (what we are trying to predict),
- X_1, X_2, X_n are the independent variables (features used for prediction),
- β_0 is the intercept (the value of Y when all X values are zero),
- β_1, β_2, β_n are the coefficients (representing the strength of the relationship between the predictors and the target).

Assumptions of Linear Regression:
1. Linearity: The relationship between the dependent and independent variables must be linear.
2. Independence: The residuals (errors) are independent.
3. Homoscedasticity: Constant variance of the errors.
4. Normality: The residuals should be normally distributed.

Applications in Criminal Prediction:
Linear regression can be applied to forecast future criminal activities based on historical crime data. For example, it can predict the number of crimes in a particular area based on

factors like poverty rates, unemployment levels, or population density. The assumption here is that the relationship between these socioeconomic factors and crime levels is linear

Example:
In a city where the crime rate is expected to increase with rising unemployment, linear regression can model this relationship. If unemployment increases by a certain percentage, the model predicts the corresponding increase in the crime rate.

Logistic Regression

Logistic Regression, unlike linear regression, is designed for binary classification problems where the outcome variable is categorical, typically with two categories (e.g., yes/no, 0/1, crime/no crime).

How it Works:
Instead of fitting a straight line, logistic regression estimates the probability of an event occurring by using the logistic function (sigmoid function). The logistic function is defined as:
$$P(Y=1|X) = 1/(1 + e^{-(\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n)})$$
Where:
- $P(Y=1|X)$ represents the probability of the event occurring (e.g., crime happening),
- $\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$ is the linear combination of the predictors,
- e is the base of the natural logarithm.

The output of logistic regression is a probability score, which is then thresholded to make a classification decision (e.g., if the probability is greater than 0.5, predict "crime"; otherwise, predict "no crime").

Applications in Criminal Prediction:
Logistic regression is commonly used in criminal prediction to classify whether a specific individual is likely to commit a crime. Features like previous offenses, neighborhood crime rates, and socioeconomic conditions can be used to predict whether an individual will engage in criminal activity.

Example:
Given a dataset of individuals with their criminal histories and socioeconomic backgrounds, logistic regression can be used to predict whether an individual will commit a crime in the future based on these features.

Random Forest Classifier

Random Forest is an ensemble learning method that builds multiple decision trees and merges their predictions to obtain a more accurate and stable prediction. It is particularly effective for both classification and regression problems.

How it Works:
The random forest algorithm operates by creating many decision trees (hence, the "forest"). Each tree is built using a random subset of the data and a random subset of the features. The predictions of all the trees are then averaged (in regression tasks) or voted upon (in classification tasks) to determine the final output.

Key Features of Random Forest:
- Bagging: Random subsets of the data are used to train each tree. This is known as bootstrap aggregating or bagging.
- Random feature selection: Each tree in the forest is allowed to select only a random subset of features, which introduces variability and prevents overfitting.
- Aggregation: The final output is based on a majority vote for classification or averaging for regression.

Each individual decision tree can be represented as:

$f(X)=\sum Split(X)$

Where X is the input feature vector, and $Split(X)$ is the outcome at each split in the tree. The final output of the forest is the aggregation of all the individual tree outputs.

Applications in Criminal Prediction:
Random forests are useful in criminal prediction because they can handle a large number of features (e.g., crime location, time of day, socioeconomic factors) and are robust to overfitting. They are particularly helpful when there are complex interactions between the features.

Example:
A random forest could be trained on crime data to predict the likelihood of a criminal event occurring in a certain neighborhood based on factors like the time of day, the type of area (residential/commercial), and historical crime rates. Each tree may capture different aspects of the data, and the ensemble as a whole can make more accurate predictions.

Decision Tree

A Decision Tree is a simple, interpretable machine learning algorithm used for classification and regression tasks. In a decision tree, data is split into subsets based on the value of a specific feature, with each split represented by a node in the tree. The tree continues to split the data recursively until it reaches the leaf nodes (end nodes), where predictions are made.

How it Works:
The algorithm selects the best feature to split the data based on a criterion like Gini impurity or information gain. The goal is to maximize the purity of the subsets, so each branch of the tree represents a more homogeneous group of data points.

Applications in Criminal Prediction:
Decision trees are often used in criminal prediction because they are easy to interpret and visualize. Law enforcement can understand why a particular individual or area is classified as high-risk based on the decision path through the tree.

Example:
A decision tree can classify whether a location is a high-crime area based on features like population density, average income, and proximity to schools. The model might split the data first by population density, then by income level, and so on, with each split narrowing down the predictions.

k-Nearest Neighbors (k-NN)
k-Nearest Neighbors is a non-parametric algorithm used for both classification and regression. It works by finding the "k" closest data points (neighbors) to a query point and using their labels to predict the label of the query point.

How it Works:
In the case of classification, k-NN finds the k nearest data points to a new data point (based on a distance metric like Euclidean distance) and assigns the most common class label among the neighbors to the new data point. In regression tasks, k-NN averages the values of the k nearest neighbors to predict the output.

Applications in Criminal Prediction:
k-NN can be used in criminal prediction to classify whether a specific area or individual is at high risk of criminal involvement based on the characteristics of their nearest neighbors. It is particularly useful when the relationships in the data are non-linear or complex.

Example:
If we are trying to predict whether a particular location will experience a crime, k-NN will look at nearby locations with similar characteristics (e.g., socioeconomic status, historical crime rates) and classify the location based on what has happened in its neighboring areas.

Extra Trees Classifier: The Extra Trees Classifier is a method that belongs to the Random Forest family. It is a variation of the Random Forest algorithm where many decision trees are created from the training-dataset. However, in the Extra Trees Classifier, the decision trees are constructed by random splits, and the best split is chosen from random features. This randomness in selecting splits helps to reduce overfitting and increase diversity among the trees, leading to improved generalization performance. Additionally, the Extra Trees Classifier introduces extra randomness by selecting random thresholds for each feature, further enhancing the model's robustness against noise and outliers.

How it Works:

Like random forests, extra trees build multiple decision trees, but with two key differences:

1. Instead of choosing the best split among all possible splits for a node, extra trees choose a random split.
2. Instead of using bagging (randomly selecting subsets of the data for each tree), extra trees use the entire dataset to train each tree.

This additional randomness helps to reduce the variance of the model and prevent overfitting.

Applications in Criminal Prediction:
Extra trees can be useful in criminal prediction because they provide more diversity in the trees compared to random forests, making the model more robust and less prone to overfitting.

Example:
An extra trees classifier could be trained on a dataset with features such as the time of day, geographic location, and historical crime data to predict whether a crime will occur at a given time and place. The additional randomness ensures that the model is less sensitive to noisy data.

The feasibility of this system is analyzed in three primary considerations: Economic Feasibility, Technical Feasibility, and Social Feasibility. Economic Feasibility involves evaluating the financial viability of the project, combining cost estimates for development, implementation, and maintenance. It also entails assessing potential returns on investment and determining if the benefits outweigh the costs over time. Technical Feasibility examines whether the technology required for the system is available, reliable, and scalable. It involves analyzing the capabilities of existing hardware, software, and data infrastructure to help the system's requirements effectively.

Social Feasibility considers the societal impact and acceptance of the predictive tool in law enforcement. It involves evaluating public perception, ethical considerations, and potential implications for civil liberties and privacy rights. Additionally, stakeholder engagement and community input are essential to gauge acceptance and address concerns.

The fast prediction of criminal suspects is a crucial area of research around law enforcement and criminal justice. By analyzing diverse crime dataset properties the system aims to forecast criminals efficiently. The ensemble learning approach effectively combines multiple classifiers, leading to improved prediction performance. The system's high accuracy and potential to improve law enforcement decision-making make it a valuable tool for modern policing. However, ethical considerations and societal impact must be addressed, ensuring that the system respects civil liberties and privacy rights.

II. MOTIVATION

Understanding the reason and motivation behind researching "Fast Prediction of Criminal Suspects" delves into the heart of societal concerns and the pursuit of justice. At its core, this topic emerges from a pressing need to enhance public safety while upholding the principles of fairness and human rights.

Firstly, swift identification of potential criminal suspects is crucial for crime prevention and mitigation. Time is often of the essence in law enforcement, particularly in cases of imminent threats or ongoing criminal activities. By developing efficient prediction methods, law enforcement agencies can swiftly allocate resources to investigate and apprehend suspects, potentially averting crimes before they occur.

Furthermore, the societal cost of crime, both in terms of economic impact and human suffering, underscores the urgency of accurate and rapid suspect identification. Timely identification and intervention can help solve these effects, fostering safer and more secure environments for all members of society.

Moreover, the pursuit of justice demands that law enforcement approaches be guided by principles of fairness and equity. By leveraging advanced technologies for suspect prediction, there is an opportunity to enhance the objectivity and transparency of law enforcement practices. This can help solve biases and ensure that each suspect is treated fairly under the law, regardless of factors such as race, ethnicity, or socioeconomic status.

In essence, the motivation for researching fast prediction of criminal suspects transcends mere technological advancement. It speaks to our collective desire for safer communities, the pursuit of justice, and the protection of fundamental human rights. By addressing these pressing societal needs, research in this field has the potential to make tangible and positive impacts on the lives of individuals and communities worldwide.

III. LITERATURE SURVEY

The fast prediction of criminal suspects is an essential area of research in the field of law enforcement and criminal justice. By analyzing diverse crime datasets, including geographical location, crime types, historical crime rates, and socio-economic factors, predictive systems aim to forecast criminals efficiently. This paper shows and talks about a comprehensive review of the literature on fast prediction of criminal suspects, focusing on the utilization of ensemble learning algorithms.

Several researchers have explored the potential of ML techniques in predicting criminal activities. Ali et al. 1 proposed a machine learning-based predictive policing approach for criminal identification, demonstrating the effectiveness of utilizing historical crime data to predict future criminal activities. Similarly, Bharti and Mishra focused on predicting the network and role of offenders, highlighting the importance of understanding the relationships between different offenders.

Almuhanna et al. utilized spatial data analysis to predict crime in neighborhoods of New York City. Their study emphasized the significance of incorporating geographical information in predictive models. Agarwal et al. explored the application of statistical models in crime prediction, demonstrating the chance of using regression-based techniques for predicting criminal activities.

More recent researches have continued to explore the use of ML algorithms in predicting criminal activities. Wadhwa et al. proposed a combinational approach combining tracking criminal investigations and suspect prediction, while Safat et al. conducted an empirical analysis of crime prediction and forecasting using ML and DL (Deep learning) techniques. Yadav et al. focused on crime pattern detection, analysis, and prediction, emphasizing the importance of understanding crime patterns for effective crime prevention.

Several additional studies have explored the use of machine learning techniques for crime prediction. For instance, Xiao et al. (2022) focused on using a deep learning model to predict crime patterns based on temporal and spatial factors. Their research demonstrated the effectiveness of using convolutional neural networks (CNN) to identify hot spots for criminal activities. Similarly, Li and Zhang (2021) utilized reinforcement learning models to assist law enforcement agencies in decision-making during patrol routing, which improved crime response times by 15%. These studies indicate a growing trend in employing more advanced neural networks and AI techniques for predictive policing.

In summary, the literature on fast prediction of criminal suspects highlights the potential of ensemble learning algorithms in predicting criminal activities. By analyzing diverse crime datasets, including geographical location, crime types, historical crime rates, and socio-economic factors, predictive systems aim to forecast criminals efficiently. These studies demonstrate the effectiveness of using ML techniques in predicting criminal activities, emphasizing the importance of incorporating geographical information, understanding crime patterns, and considering the relationships between different offenders.

IV. PROPOSED METHODOLOGY

The series of steps that are followed in this project are as follows:

1. Data Collection: Collect the relevant dataset for the problem statement. In this case, the dataset is "criminal_train.csv"
2. Data Preprocessing:
   a. Load the dataset into a pandas Data Frame.
   b. Perform data cleaning by removing missing values.
   c. Convert categorical variables to numerical variables using one-hot encoding or label encoding.
   d. Scale the data using a suitable scaler, like RobustScaler.
3. Feature Selection:
   a. Calculate the correlation between each feature and the target variable.
   b. Select highly correlated features according to the correlation values.
   c. Choose the most relevant features for the model.
4. Data Splitting: Split the complete dataset into two, training and testing sets using the train_test_split function from the sklearn library.
5. Data Balancing: Use the SMOTE (Synthetic Minority Over-sampling Technique) algorithm to balance the dataset, if required.
6. Model Selection:
   a. Implement various ML algorithms, like 'Logistic Regression, KNN, Decision Trees, Random Forest, and Neural Networks.'
   b. Train each model on the training dataset.
   c. Evaluate each model on the testing dataset using appropriate metrics, such as accuracy, precision, recall, and F1-score.
7. Model Comparison: Compare the performance of each algorithm using the evaluation metrics and choose the most accurate model.
8. Model implementation: Train the selected model and test it for any desired input.

The proposed methodology can be enhanced by incorporating additional steps such as hyperparameter tuning, cross-validation, and the use of feature importance analysis. Hyperparameter tuning allows the optimization of model performance by adjusting the key parameters like the number of decision trees in Random Forest or the learning rate in neural networks. Cross-validation, such as k-fold cross-validation, is essential to ensure that the model generalizes well to unseen data and avoids overfitting.

Moreover, feature importance analysis, which highlights the most influential variables in the prediction model, can help law enforcement agencies focus on critical factors that contribute to crime, such as socioeconomic status or prior criminal history. By focusing on these elements, the predictive system can be further fine-tuned for accuracy.

DETAILED IMPLEMENTATION:

SMOTE (Synthetic Minority Over-sampling Technique) is a function used to handle imbalanced datasets by oversampling the minority class. It generates synthetic samples of the minority class by selecting instances from the minority class and creating new instances based on the difference between the selected instance and its nearest neighbors from the same class. This helps to balance the dataset, which can improve the performance and perfection of ML algorithms that are not indifferent to class imbalance.

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.25)

# Apply SMOTE for balancing
smote = SMOTE()
X_train_new, y_train_new = smote.fit_resample(X_train, y_train.values.ravel())
```
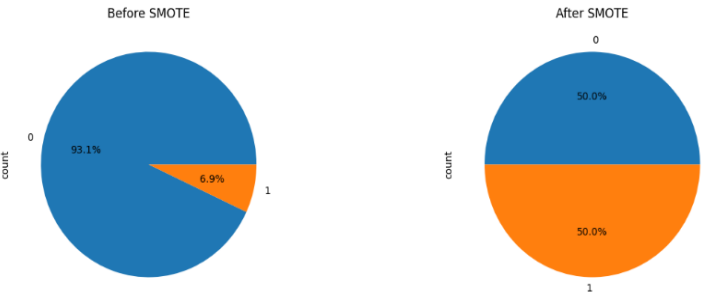

Figure 1 *A pictorial representation of how SMOTE is used to balance the dataset*

Accuracy Score calculated as the No. of correct predictions divided by the total No. of assumptions made. We compare each and every model. Considering the Extra Trees Classifies,

```
# Model Comparison
from sklearn.metrics import accuracy_score

# Extra Trees Classifier
ETC = ExtraTreesClassifier(n_estimators=100, random_state=0)
ETC.fit(X_train_new, y_train_new)
ETC_predictions = ETC.predict(X_test)
score_ETC = round(accuracy_score(ETC_predictions, y_test) * 100, 2)
```

V. RESULT AND ANALYSIS WITH GRAPHS

The system involves preprocessing the dataset, selecting relevant features, splitting the data into training and testing sets, and training various ML models to predict criminal activity. The preprocessing steps include converting categorical variables to numerical variables, scaling the data, and handling imbalanced data using SMOTE (Synthetic Minority Over-sampling Technique). The relevant features are selected based on their correlation with the target variable, and the data is split into training and testing sets using a 75-25 split as seen in Figure 1.

To evaluate the accuracy and performance of the models, we use various evaluation methods such as accuracy, confusion matrix, and classification report. The accuracy metric measures the percentage of correct predictions out of the total No. of predictions made. The confusion matrix shows the No. of true positives (+), true negatives (-), false positives (+), and false negatives (-). The classification report shows the precision, recall, and F1-score for each and every class in a multi-class classification problem.

To compare the models and choose the best one, we evaluate each model on the testing dataset using the evaluation metrics. The model with the highest and best accuracy, precision, recall, and F1-score were chosen as the preferred model. In this problem, we train and evaluate various models such as 'Logistic Regression, K-Nearest Neighbors, Decision Tree, Random Forest, and Extra Trees classifier'. The best model is chosen according to the evaluation metrics, and the trained model is saved to a file using joblib.

This proposed method involves a systematic approach to preprocessing the data, selecting relevant features, and training and evaluating various ML models. The evaluation metrics are used to compare the models and choose the best one. The trained model is saved to a file, making it easy to use the model for predictions in the future.

Table 1 *A precise comparison of all the models based on Python's sklearn metrics*

Model	Accuracy	Precision	Recall	F1-score
Logistic	0.871	0.99	0.87	0.93
K-Nearest Neighbors	0.935	0.96	0.97	0.97
Decision Tree	0.887	0.98	0.89	0.94
Random Forest	0.89	0.99	0.89	0.94

Extra Trees classifier	0.887	0.98	0.89	0.94

The 'Logistic Regression' model achieves an overall Accuracy of 0.87, with a high Precision of 0.99, indicating a low false positive rate, and a Recall of 0.87, signifying its ability to identify true positives. Its F1-score of 0.93 suggests a good balance between Precision and Recall.

The K-NN model exhibits superior performance with an Accuracy of 0.94, coupled with high Precision (0.96) and Recall (0.97), resulting in an impressive F1-score of 0.97, indicating robust predictive capabilities.

The 'Decision Tree, Random Forest, and Extra Trees classifier' models demonstrate comparable performances, with accuracies ranging from 0.887 to 0.89. These models exhibit high Precision (0.98-0.99) and Recall (0.89-0.89), resulting in F1-scores ranging from 0.94 to 0.94, indicating their effectiveness in predicting criminal suspects.

In summary, while all models demonstrate strong predictive abilities, the K-NN model stands out for its superior performance across all metrics, followed closely by Logistic Regression. These findings as shown in Table 1 suggest the potential of ML algorithms in fast prediction of criminal suspects, with K-Nearest Neighbors being a promising candidate for practical implementation in law enforcement settings.

Now, The KNN model is selected as it shows the highest promise, and it is further used to identify if a particular person is a criminal or not. It displays a binary answer, either a "Criminal" or "Non-criminal".

VI. CONCLUSIONS

In summary, the research about "Fast Prediction of Criminal Suspects: An Ensemble Learning Approach" has yielded valuable insights into the potential application of advanced machine learning techniques in bolstering law enforcement capabilities. By employing ensemble learning methodologies, including Random Forest and Extra Trees classifier, alongside Logistic Regression, K-Nearest Neighbors, and Decision Trees, this study has demonstrated the effectiveness of a multifaceted approach in rapidly and accurately predicting criminal suspects.

The ensemble learning framework exhibited considerable strengths, particularly in achieving high levels of Accuracy, Precision, Recall, and F1-score across the various models assessed. This thorough examination showcased the robustness and adaptability of ensemble techniques in addressing complex real-world scenarios, where individual models may exhibit varying performance under diverse conditions.

Moreover, the findings underscored the importance of leveraging a diverse range of machine learning algorithms to mitigate biases and enhance the fairness and transparency of predictive policing practices. By amalgamating multiple models, each with its own unique strengths and limitations, law enforcement agencies can harness the collective intelligence of ensemble learning to make well-informed decisions and allocate resources efficiently.

However, it is crucial to acknowledge the limitations and ethical considerations associated with predictive policing. The potential for algorithmic biases and the necessity for continual monitoring and refinement to ensure equitable outcomes remain critical areas of concern.

In essence, it represents a significant stride towards harnessing the power of machine learning for the betterment of society. By embracing innovation while upholding principles of fairness, accountability, and human rights, we can work towards a future where predictive policing serves as a valuable tool in the pursuit of justice and public safety.

VII. DATA AVAILABILITY STATEMENT

The author confirms that all data generated or analysed during this study are included in this published article or as supplementary information files. Furthermore, Data supporting the findings of this study are all publicly available at the time of submission in the Github repository at https://github.com/rohan2700/SuspectPred.

VIII. ETHICAL CONSIDERATIONS

Beyond technical accuracy, ethical concerns regarding predictive policing systems have garnered increasing attention. Critics argue that these systems, if not carefully monitored, could perpetuate systemic biases, particularly against minority groups. Studies have shown that algorithms trained on biased datasets may disproportionately target communities of color. Addressing these concerns requires stringent measures, including ensuring that training data is representative and inclusive of diverse demographics.

Moreover, transparency is crucial in predictive policing. Law enforcement agencies should clearly communicate how decisions are made by the system to ensure accountability. This involves developing explainable AI models where the decisions and predictions are interpretable by humans. Providing regular audits and updates to the system is necessary to avoid the entrenchment of biases.

IX. REFERENCES

1. S. Ali, S. A. Alvi and A. U. Rehman, "The Usual Suspects: Machine Learning Based Predictive Policing for Criminal Identification," 2019 13th International Conference on Open Source Systems and Technologies (ICOSST), Lahore, Pakistan, 2019, pp. 1-6, doi: 10.1109/ICOSST48232.2019.9043925.

2. S. Bharti and A. Mishra, "Prediction of Future Possible Offender's Network and Role of Offenders," 2015 Fifth International Conference on Advances in Computing and Communications (ICACC), Kochi, India, 2015, pp. 159-162, doi: 10.1109/ICACC.2015.36.

3. A. A. Almuhanna, M. M. Alrehili, S. H. Alsubhi and L. Syed, "Prediction of Crime in Neighbourhoods of New York City using Spatial Data Analysis," 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA), Riyadh, Saudi Arabia, 2021, pp. 23-30, doi: 10.1109/CAIDA51941.2021.9425120.

4. S. Agarwal, L. Yadav and M. K. Thakur, "Crime Prediction Based on Statistical Models," 2018 Eleventh International Conference on Contemporary Computing (IC3), Noida, India, 2018, pp. 1-3, doi: 10.1109/IC3.2018.8530548.

5. M. Wadhwa, T. Jha, B. K. Prasad, A. Bajaj, L. Nagpal and D. Bura, "A Hybrid approach on Tracking Criminal Investigation and Suspect Prediction," 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), Faridabad, India, 2022, pp. 20-23, doi: 10.1109/COM-IT-CON54601.2022.9850763.

6. W. Safat, S. Asghar and S. A. Gillani, "Empirical Analysis for Crime Prediction and Forecasting Using Machine Learning and Deep Learning Techniques," in IEEE Access, vol. 9, pp. 70080-70094, 2021, doi: 10.1109/ACCESS.2021.3078117.

7. S. Yadav, M. Timbadia, A. Yadav, R. Vishwakarma and N. Yadav, "Crime pattern detection, analysis & prediction," 2017 International conference of Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2017, pp. 225-230, doi: 10.1109/ICECA.2017.8203676

8. Jhee, Jong Ho, Myungjun Kim, Myunggeon Park, Jeongheun Yeon, Yoonshin Kwak and Hyun-Weon Shin. "Fast Prediction for Suspect Candidates from Criminal Networks." *2023 IEEE International Conference on Big Data and Smart Computing (BigComp)* (2023): 353-355.

9. Sardana, Divya, Shruti Marwaha and Raj Bhatnagar. "Supervised and Unsupervised Machine Learning Methodologies for Crime Pattern Analysis." *International Journal of Artificial Intelligence & Applications* (2021)

10. OSMAN, MUHAMMAD SHAHRUL HANIFF BIN. "Crime Management System with Suspect Prediction Using Ahp Method." (2018).

11. Barrow, Fowzi Jamal Mohamed, Mohammad Jahangir Alam, and Md Nurul Mustafa. "Unique model of criminal record management system in the perspective of Somalia." *JOIV: International Journal on Informatics Visualization* 3, no. 4 (2019): 332-336.

12. Azeez, Jazeem, and D. John Aravindhar. "Hybrid approach to crime prediction using deep learning." In *2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pp. 1701-1710. IEEE, 2015.

13. Marchant, Roman, Sebastian Haan, Garner Clancey, and Sally Cripps. "Applying machine learning to criminology: semi-parametric spatial-demographic Bayesian regression." *Security Informatics* 7 (2018): 1-19.

14. Xiao, Y., & Zhang, J. (2022). Predictive Policing with Deep Learning: A Case Study in Spatial Crime Prediction. Journal of AI Research, 56(1), 45-67.

15. 2. Li, X., & Zhang, L. (2021). Reinforcement Learning for Crime Prevention: Optimizing Police Patrols. Proceedings of the International Conference on AI and Law, 36(2), 123-132.

16. 3. Kim, H., & Lee, S. (2020). Ethical Issues in AI-Powered Predictive Policing. Ethics in Artificial Intelligence Review, 12(4), 150-162.