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Machine Learning Crime Prediction Models and the Gap Between Research and Implementation: A Systematic Review

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Keywords

Machine learning, deep learning, supervised learning, feature selection, classification and regression, predictive models, predictive analytics, crime prediction.

REVIEW ARTICLE

Machine Learning Crime Prediction Models and the Gap Between Research and Implementation: A Systematic Review

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A crime is an illegal or violent act committed by one individual against another. The increasing crime rate has become a major concern as it negatively affects people's quality of life and generates significant social and economic costs. This study aims to identify the most widely used machine learning (ML) models for crime prediction, determine evaluation metrics for assessing model performance, and analyze key data characteristics to enhance real-world implementation. The study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. A search string was formulated using the population, intervention, comparison, and outcomes (PICO) framework and applied to the Scopus and Web of Science database. After applying eligibility criteria, 50 articles were selected for in-depth analysis. The findings indicate that the most prominent ML models include extreme gradient boosting (XGBoost), random forest (RF), gradient boosting decision trees (GBDT), and auto-regressive integrated moving average (ARIMA), as well as deep learning models such as long short-term memory (LSTM), which showed high performance in dynamic urban environments. The most relevant metrics for classification are accuracy, recall, F1-score, precision, and area under the curve (AUC), while for regression, mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R^2) are preferred. Key data features include date, time, age, gender, education level, location, and coordinates. Additionally, integrating climate and temperature data is recommended. This study provides a structured analysis of crime prediction models and proposes an architecture for their development and deployment, offering valuable insights for future research and practical applications.

Keywords: Machine learning, Deep learning, Supervised learning, Feature selection, Classification and regression, Predictive models, Predictive analytics, Crime prediction

1. Introduction

Crime is defined as an illegal or violent act committed by one individual against another, potentially causing harm to people and property. Such conduct is subject to legal sanctions according to the laws of the state or the authority governing the place where the offense occurs [1]. In recent years, the rising number of reported criminal incidents, along with the increasing volume of crime-related data, has made manual processing by individuals and organizations increasingly difficult [2]. Crime prevention and public safety remain critical societal concerns worldwide [3]. Predicting high-risk urban crime areas is essential to maintaining public safety and promoting sustainable development [4].

Crime rates continue to rise globally, manifesting in various forms such as robbery, theft, drug offenses, murder, and illicit trafficking—issues that are cause for serious concern [5]. In many cities, population growth has coincided with an increase in crime rates, while security measures have not kept pace [6]. Factors including politics, economy,

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culture, education, employment, traditional beliefs, and legal systems often influence the distribution of crime in urban areas. The presence of crime negatively affects quality of life and contributes to broader social challenges, imposing significant costs on both public and private sectors [7].

In this context, crime in India has seen a marked increase over time. According to data from the National Crime Records Bureau (NCRB), an average of 8837 offenses under the Indian Penal Code (IPC) were reported daily in 2019. In 2020, IPC case filings increased by more than 430% compared to the same period the previous year. In 2022, violent crimes included 28,522 murders and 107,588 cases of kidnapping and abduction, with crime rates of 66.4 per 100,000 women and 36.6 per 100,000 children, reflecting a persistent rise in criminal activity nationwide [8−10]. In England and Wales, police-recorded crime rose by 13%, particularly in offenses involving violence, weapons, sexual assaults, and personal attacks [11]. Additionally, recidivism significantly impacts public safety and incarceration costs. A 2016 study in England and Wales estimated recidivism-related costs at £18.1 billion, with international estimates placing the recidivism rate at approximately 50% [12]. According to a United Nations report, although crime has declined in some developed regions, such as North America and Western Europe, it has risen in areas like Africa and Latin America. Notably, 60% of urban residents in developing countries have been victims of crime, with some cities in these regions reporting victimization rates as high as 70% over five years [13].

Crime is closely linked to socioeconomic factors, particularly unemployment, creating a cycle where people with criminal records face employment restrictions, increasing crime rates [14]. This urban crime imposes significant economic and social burdens, necessitating policies that enhance public safety [7,15]. Law enforcement and policymakers are focusing on crime prevention by optimizing resources and addressing the drivers of crime, including politics, economics, education, and demographics [3]. Furthermore, these factors are being investigated in Malaysia, using crime data from the Royal Malaysian Police and Meteorological Department from 2011 to 2020 [16]. Crime also influences personal and business decisions, impacting relocation, travel, and security investments. Consequently, governments, businesses, and individuals must allocate significant resources to law enforcement, judicial procedures, and other security mechanisms [11]. Addressing these challenges requires data-driven solutions for effective crime prevention.

With the continued rise in crime rates, it is crucial to address the associated problems immediately. The accelerated increase in criminal activity necessitates that law enforcement and justice agencies implement effective measures to control and reduce it. Despite the abundance of data available, predicting crimes and identifying those responsible remains a significant challenge for police departments [16]. As [17] points out, **crime is difficult to predict because it is unpredictable and can occur at any time and place, posing a significant challenge to society.**

In recent years, interest in applying mathematical and statistical methods for crime prediction has grown considerably, enabling more proactive policing strategies [3]. Reliable data combined with robust statistical models provides critical insights that improve the allocation of police resources, as demonstrated in Rio de Janeiro's Public Security Secretariat, where crime patterns are analyzed to optimize police deployment [18]. Given that crime rates and types vary significantly across regions, this remains a persistent global challenge [5,16]. To address these complexities, machine learning has emerged as a valuable tool, strengthening law enforcement's capacity to anticipate and prevent criminal activity [8].

Crime prediction has evolved from basic analysis methods to sophisticated approaches incorporating machine learning and deep learning. These models integrate crime data with demographic, economic, and social information to generate more precise predictions, allowing for a deeper understanding of crime patterns and more effective prevention strategies [19]. However, the effectiveness of crime prevention efforts may be compromised when applied rigidly, without taking into account the unique dynamics of different urban settings [20].

Multiple factors influence crime rates and evolve over time, making data-driven approaches essential. Algorithms such as simple linear regression (SLR), multiple linear regression (MLR), decision tree regression (DTR), support vector regression (SVR), and random forest regression (RFR) are widely used to estimate crime incidents [8]. Additionally, time series techniques like ARIMA and SARIMA have proven effective in forecasting crime based on historical data [21]. Spatiotemporal prediction is also critical, as it enables the identification of potential crime hotspots by integrating historical data, environmental variables, and demographic characteristics through statistical and machine learning methods [22]. These models not only enhance crime hotspot mapping but also support targeted, data-driven interventions [4].

Nowadays, obtaining and analyzing crime data is essential. Crime data can be identified by several factors, such as the event's location, the time when the crime was detected, and the prediction of their future relationship, which is essential in a crime prevention system. According to research by Ref. [23], time and place are crucial in identifying crime patterns. Machine learning techniques enable the extraction of valuable information from collected datasets and the identification of relationships between crime, place, and time. Many researchers have pointed out that detecting crime patterns is a critical and time-consuming task, which [23] suggests **can be solved by machine learning techniques**.

However, despite these promising advances, the application of machine learning to crime prediction in real-world contexts faces significant challenges. These include limited access to quality data, biases in datasets and algorithms, and ethical concerns regarding surveillance and privacy. A critical limitation also lies in the lack of understanding of the contextual realities and data structures within institutional systems. Technical expertise alone is insufficient; effective modeling requires domain knowledge of how and why the data were generated. These barriers help explain the persistent gap between academic research and practical implementation in public safety systems.

This study arises from the need to know and determine the most recent advances in crime prediction. It seeks to identify advances in machine learning, real-world cases treated, the results obtained, and the difficulties and limitations in this thematic area. In addition, the results obtained have important implications in the academic world, particularly in decision-making that relies on evidence and updated, rigorously examined information, as well as in state agencies and institutions responsible for public security, policymakers, and justice administration entities. This study is structured in sections. Section II is presented below, where the methodology and process used to obtain the inputs for the systematic review are described. In Section III, the results obtained are presented, along with a proposal resulting from the reviews and the respective discussions. Finally, the conclusions obtained, and future works are given in Section IV.

2. Method

This article adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to ensure a rigorous and transparent systematic review process. This approach provides a structured guide that allows researchers to reduce bias and communicate results more clearly and comprehensively, facilitating replicability and usefulness for the scientific community and other interested users [24,25]. The PRISMA methodology was implemented to identify, select, and analyze relevant articles, ensuring compliance with defined inclusion and exclusion criteria. This structured approach enables an objective and reliable assessment of the available literature, thereby contributing to the quality and accuracy of the results obtained in research on crime prediction using machine learning.

2.1. Research questions

Today, emerging technologies such as machine learning are significantly transforming strategies for crime prediction and prevention [19]. This article conducts a systematic review of the literature, employing the PRISMA methodology to assess the effectiveness of predictive models in this field. Tables 1 and 2 also present a detailed breakdown of

Table 1. PICO approach.

Components	Questions	Description
P (Population/Problem)	What is the problem being addressed, and who is the population of interest?	There is a need to identify the most effective machine learning models for crime prediction, taking into account the characteristics of the data used and their implementation in real-world contexts.
I (Intervention)	What intervention or approach will be evaluated or considered?	The application of machine learning models for crime prediction involves assessing their accuracy and effectiveness using specific metrics.
C (Comparison)	What will the intervention be compared to?	Comparison between different machine learning models, their approaches, the characteristics of the data used, and their applicability in real environments.
O (Outcome)	What results are expected to be observed or measured?	Identify the most accurate and effective models for crime prediction, analyze the evaluation metrics used, and understand the conditions necessary for their practical implementation.

Table 2. Research questions.

N°	Code	Research Questions
1	RQ1	What are the most used machine learning models for crime prediction, and which have been proven most effective based on evaluation metrics?
2	RQ2	What evaluation metrics do machine learning models use in crime prediction?
3	RQ3	What data features are most relevant to improving the accuracy of machine learning models in crime prediction?
4	RQ4	In what real-life context have machine learning based crime prediction models been implemented, and what have been the main challenges?

the research questions formulated under the PICO framework (problem, intervention, comparison, and outcome), providing a clear structure for the analysis.

2.2. Search strategy

The PICO approach was used as a search strategy, facilitating the construction and organization of the search string based on its key components and the questions outlined in Tables 1 and 2. Table 3 presents the details of the elements that make up this framework, along with the selected keywords and terms used in formulating the search string.

The main search string is built once the keywords and search strings have been identified. First, the boolean operator "OR" is used with each keyword in each component respectively; finally, the "AND" is used with all the PICO components according to their coding {(PRO) AND (INT) AND (COM) AND (OUT)}. The resulting search equation to be used is:

For Scopus:

TITLE-ABS-KEY (("crime prediction" OR "crime detection" OR "prediction of crime" OR "crime prevention" OR "crime forecasting" OR "crime analytics" OR "crime analysis" OR "crime rate") AND ("machine learning" OR "learning machine" OR "transfer learning" OR "unsupervised learning" OR "supervised learning" OR "reinforcement learning" OR "neural network*" OR "deep learning" OR "artificial intelligence") AND ("feature" OR "data set" OR "dataset" OR "data features" OR "attributes" OR "variables" OR "data collection") AND ("metrics" OR "evaluation metrics" OR "model performance" OR "precision" OR "accuracy" OR "recall" OR "F1-score" OR "AUC" OR "ROC curve" OR "confusion matrix" OR "mean squared error" OR "MSE" OR "mean absolute error" OR "RMSE" OR "cross-validation")).

For Web of Science:

TS=(("crime prediction" OR "crime detection" OR "prediction of crime" OR "crime prevention" OR "crime forecasting" OR "crime analytics" OR "crime analysis" OR "crime rate") AND ("machine learning" OR "learning machine" OR "transfer learning" OR "unsupervised learning" OR "supervised learning" OR "reinforcement learning" OR "neural network*" OR "deep learning" OR "artificial intelligence") AND ("feature" OR "data set" OR "dataset" OR "data features" OR "attributes" OR "variables" OR "data collection") AND ("metrics" OR "evaluation metrics" OR "model performance" OR "precision" OR "accuracy" OR "recall" OR "F1-score" OR "AUC" OR "ROC curve" OR "confusion matrix" OR "mean squared error" OR "MSE" OR "mean absolute error" OR "RMSE" OR "cross-validation")).

2.3. Eligibility criteria

Inclusion and exclusion criteria were applied to ensure a comprehensive and systematic review of the literature. These criteria helped guarantee that the selected studies were relevant, high-quality, and aligned with the research objectives. Table 4 outlines the specific parameters used to select or

Table 3. Search terms.

PICO	Code	Keywords	Search string (Synonyms)
P	PRO	Crime, crime prediction	"crime prediction" OR "crime detection" OR "prediction of crime" OR "crime prevention" OR "crime forecasting" OR "crime analytics" OR "crime analysis" OR "crime rate".
I	INT	Machine learning, artificial intelligence	"machine learning" OR "learning machine" OR "transfer learning" OR "unsupervised learning" OR "supervised learning" OR "reinforcement learning" OR "neural network*" OR "deep learning" OR "artificial intelligence"
C	COM	Feature, dataset	"feature" OR "data set" OR "dataset" OR "data features" OR "attributes" OR "variables" OR "data collection"
O	OUT	Metrics, evaluation metrics	"metrics" OR "evaluation metrics" OR "model performance" OR "precision" OR "accuracy" OR "recall" OR "F1-score" OR "AUC" OR "ROC curve" OR "confusion matrix" OR "mean squared error" OR "MSE" OR "mean absolute error" OR "RMSE" OR "cross-validation"

Table 4. Exclusion and inclusion criteria.

Eligibility criteria	Code	Search string
Exclusion	E1	Articles published before 2020
	E2	Conference papers
	E3	Non-English language articles
	E4	Full text articles not available
Inclusion	I1	Articles related to crime prediction
	I2	Articles about forecasting
	I3	Journal articles with impact factor
	I4	Articles containing datasets

discard articles during the screening process. Given the rapid evolution of crime patterns, the review focused on recent techniques, including only articles published from 2020 onward, to emphasize modern approaches that address current challenges in crime prediction.

2.4. Information sources

Various digital platforms are designed to search, group, and organize scientific literature; the most popular and used are Scopus, Web of Science, and Google Scholar [10]. Scopus is now an exhaustive thematic classification platform, making it a valuable resource for multidisciplinary research and searching [26]. On the other hand, Web of Science guarantees a high standard in its publications but presents a more reduced bibliographic coverage [27]. However, Google Scholar presents several obstacles and challenges regarding the accuracy of citation counting, which can affect the research impact assessment [28].

Several studies have compared the coverage of journals across different databases, concluding that Scopus offers the optimal number of publications to conduct precise and exhaustive analyses across a wide range of disciplines. Likewise [10], conducted a scientometric analysis on crime prediction in his research, recommending the use of Scopus for this type of analysis. In this sense, the Scopus and Web of Science databases were used as a source of information in this study (See Fig. 1).

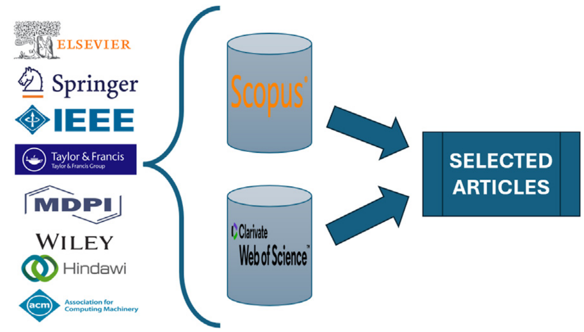

Fig. 1. Information sources.

2.5. Article selection process

The article selection followed four phases, as outlined in the PRISMA guidelines. Initially, 530 records were retrieved using the defined search string without filters. A first filter was applied to limit results to “Article Title, Abstract, and Keywords” fields. After removing duplicates and applying inclusion and exclusion criteria, titles, abstracts, and full texts were screened to select the most relevant studies. The whole process is detailed in Fig. 2.

3. Results and discussion

To address the research questions defined in Table 2, a systematic data extraction process was applied to the 50 selected articles. Each article was reviewed in full to collect structured information aligned with the four core questions. The extracted data were organized into comparative summary tables (Tables 5−9), which include indicators such as model usage frequency, performance scoring, classification vs. regression metrics, dataset sources, and variables, as well as practical application cases. This consistent extraction enabled a transparent cross-study comparison, allowing for the identification of trends, strengths, and gaps in current crime prediction research. The process was conducted manually and verified for consistency to ensure alignment with the review's methodological rigor.

A. *RQ1. What are the most used machine learning models for crime prediction, and which have been proven most effective based on evaluation metrics?*

Table 5 lists all the models examined in the 50 articles selected for this review. It includes a scoring column that reflects each model's performance; a higher score indicates better performance in more studies, while a score of zero means the model was used but did not demonstrate outstanding results.

Regarding the question, it can be highlighted that the most used models are random forest, support vector machine, decision tree, k-nearest neighbor, Naive Bayes, extreme gradient boosting (XGBoost), and logistic regression; however, of this group, those that have proven to be most effective are XGBoost and random forest, this for machine learning. On the other hand, it has been identified that deep learning models are being heavily incorporated for crime prediction, either individually or in conjunction with machine learning models as hybrid models. Long

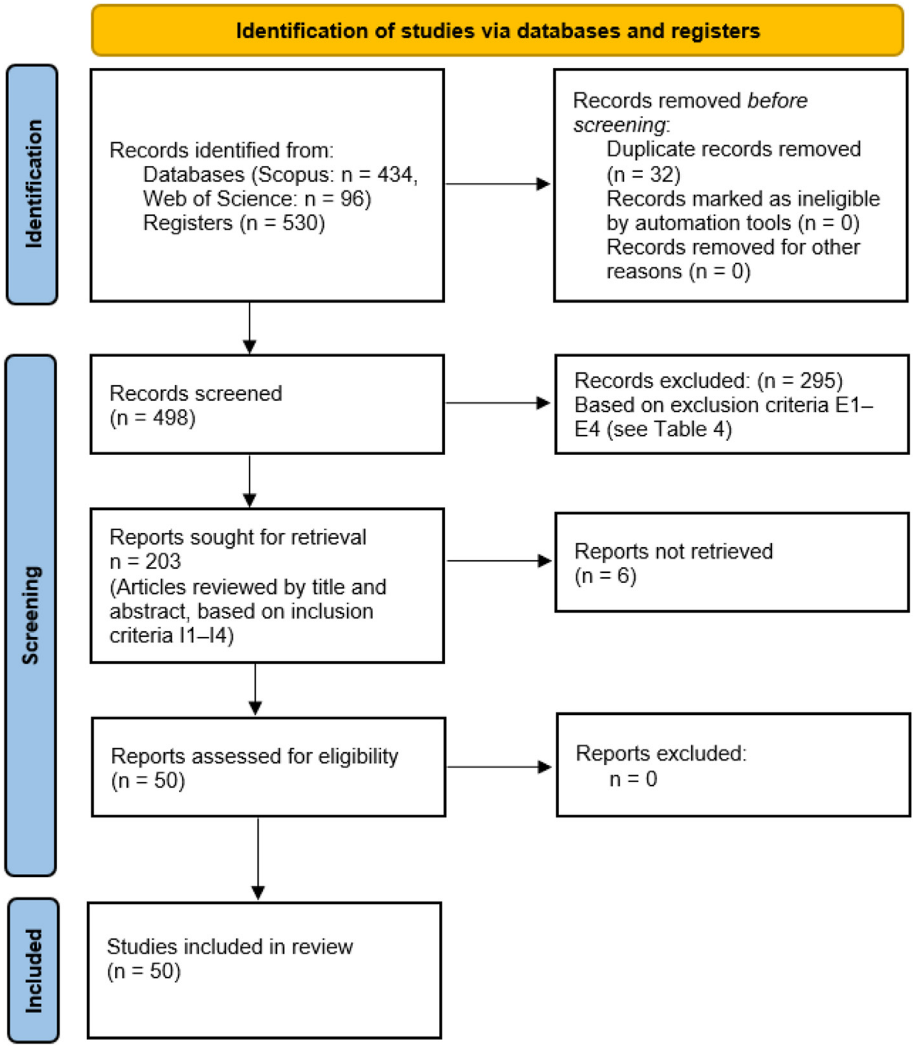

Fig. 2. Study selection process (PRISMA).

short-term memory (LSTM) and deep neural network (DNN) are the most widely used and best-performing models in this group. Finally, a group of hybrid models developed by the authors in their respective research has been identified. Regarding this, it is necessary to generate experimental environments with similar data sets and new characteristics in the data to test and validate the effectiveness of these models in various scenarios. The above information can be found in Table 6, where the most used models are listed in order of performance. Table 7 also illustrates the techniques employed to enhance the performance of the models.

B. RQ2. What evaluation metrics do machine learning models use in crime prediction?

Table 8 presents the most used evaluation metrics and their frequency across the reviewed articles. It also includes a column that distinguishes whether the metric is used for classification (C) or regression (R), as well as another indicating the highest performance value achieved and the model that obtained it. In addition to the metrics listed in Table 8, other relevant measures were identified in specific studies, such as the Pearson Correlation Coefficient (PCC), Predictive Accuracy Index of Raster (PAIR) [60], execution time, memory usage, training and testing time [5], Predictive Accuracy Index (PAI), Predictive Efficiency Index (PEI), Recapture Rate Index (RRI) [37], Jensen–Shannon Divergence (JSD), and Total Variational Distance (TVD) [55].

Fig. 3 provides a visual summary of the top-performing models, as evaluated by the metrics reported across the reviewed studies. Each point represents a model and the metric where it achieved its highest performance. The color indicates the model type (machine learning, deep learning, or hybrid), while the marker shape distinguishes whether the model is among the most frequently

Table 5. Machine learning models used.

Models/Algorithms	Score	Article
Generalized Linear Model (GLM)	0	[16]
Random Forest (RF)	10	[16,17,29–43,66–68,72–76]
Decision Tree (DT)	0	[16,23,29–34,69,72–74]
Gradient Boosting Decision Tree (GBDT)	3	[16,17,42]
Support Vector Machine (SVM)	1	[5,16,23,33,35,38,41,42,44,45,68–70,73,75]
K-Nearest Neighbor (KNN)	0	[29,32–34,37,39,41,46,69]
Long Short-Term Memory (LSTM)	2	[33,47–50,68,70,71]
AutoRegressive Integrated Moving Average (ARIMA)	1	[33,47,49,68]
Logistic Regression (LR)	0	[23,30,33,42,43,45,70,73,74]
XGBoost	7	[11,30,33,36,37,51,52,68,72,74,75]
Gaussian Naïve Bayes (NB)	2	[17,23,33,34,38,39,41,46,67,69]
Stochastic Gradient Descent (SGD)	1	[23]
Artificial Neural Network (ANN)	0	[5,42]
Hybrid Classifier (SVNN) (combination of SVM and ANN)	1	[5]
Deep Neural Networks (DNN)	2	[5,45,51]
CatBoost	0	[36,72]
LightGBM	3	[36,43,53,72]
GSCA (Generalized Structured Component Analysis)	0	[48]
TwitterGuard	0	[48]
ConvBiLSTM (Convolutional Bidirectional LSTM)	0	[48]
SocioCrimAnalytix	0	[48]
CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory)	0	[48]
DAC-BiNet (Dual Attention-Compensated Bidirectional Network)	0	[48]
LSA (Latent Semantic Analysis)	0	[48]
LSTMTwitter (LSTM for Twitter Data)	0	[48]
MDL (Minimum Description Length)	0	[48]
Reinforcement Learning	1	[48]
Genetic algorithm (GA)	0	[5]
FireFly (FF)	0	[5]
Particle Swarm Optimization (PSO)	0	[5]
Linear regression	0	[37,46]
Convolutional Neural Network (CNN)	1	[38,39,46,68]
Hybrid model CNN-LSTM	1	[54]
Seasonal Auto-Regressive Integrated Moving Average (SARIMA)	0	[49]
Attention based Interpretable Spatio Temporal Network (AIST)	1	[55]
Stacking	0	[38]
Lazy: IBK	0	[38]
Bagging	0	[38,75]
Locally weighted learning	0	[38]
Deep Convolutional Extreme Gradient Boosting (DeCXGBoost)	2	[38,39]
Neural Attentive Framework for Hour-Level (NAHC)	0	[45]
ANN+BERT (Artificial Neural Network con BERT)	0	[45]
ConvBiLSTM (Convolutional Bidirectional Long Short-Term Memory)	1	[45]
Gated Recurrent Unit (GRU)	0	[56,70]
Attention (Attn)	0	[56]
Graph Convolutional Network (GCN)	0	[56]
Graph Gated Convolution (GGConv)	0	[56]
Neighborhood Convolution (NbConv)	1	[56]
Stacked Bidirectional LSTM (St-Bi-LSTM)	0	[50]
Fusion Model (LSTM y Bidirectional LSTM)	1	[50]
Bidirectional Encoder Representations from Transformers (BERT – BERT12multi)	0	[57]
Hybrid Attention-CNN (HAC)	1	[57]
Hybrid Model N-Beats (RNN-LSTM)	1	[58]
Multilayer Perceptron (MLP)	0	[33,53]
SBCPM (Stack-Based Crime Prediction Model) – (SVM, J48, and C4.5)	1	[59]
ST-Cokriging (Space-Time Cokriging)	1	[60]
Poisson regression	0	[53]
Geographically Weighted Random Forest (GWRF)	1	[66]
Additive regression	1	[67]
Integrated graph model	1	[68]
2D-CNN combined with SoftMax	1	[69]
DeePrison	1	[70]
Federated LSTM	1	[71]
Extra tree regression	1	[75]

Table 6. Most used models with the best results.

Type	Models
Machine learning	XGBoost
	Random Forest (RF)
	Gradient Boosting Decision Tree (GBDT)
	LightGBM
	Gaussian Naïve Bayes (NB)
	Support Vector Machine (SVM)
	AutoRegressive Integrated Moving Average (ARIMA)
	Stochastic Gradient Descent (SGD)
Deep learning	Long Short-Term Memory (LSTM)
	Deep Neural Networks (DNN)
	Deep Convolutional Extreme Gradient Boosting (DeCXGBoost)
Hybrid models	The hybrid and proprietary models found are interesting options for replication and performance improvement; however, their effectiveness will depend on the dataset for which they are intended.

used in recent literature. This visualization allows for a quick comparison of model effectiveness and popularity, highlighting both widely adopted and high-performing emerging approaches.

C. *RQ3. What data features are most relevant to improving the accuracy of machine learning models in crime prediction?*

The performance of machine learning models in crime prediction depends mainly on the characteristics, variables, or attributes considered in the datasets used. A fundamental aspect is the volume of data, since an extensive dataset allows for capturing more representative patterns, reducing bias, and increasing the model's ability to generalize. In addition, the quality of the dataset is crucial, with data from reliable sources such as police departments, government entities, and open data platforms being preferred.

In Table 9, the most relevant characteristics used in the reviewed articles can be observed. This table shows the city and origin from which the data were obtained, the type of crime, the characteristics, and the number of records in the dataset. The characteristics that stand out the most are the date and time, geographic location (including coordinates, latitude, and longitude), and characteristics related to the crime, the offender, and the victim; interesting characteristics such as climate and temperature have also been included. These variables provide essential context for identifying complex correlations and existing patterns in criminal activity. Additionally, including broad and recent time ranges facilitates the detection of historical and seasonal trends, thereby increasing the predictive capacity of the models. In summary, optimal datasets for predicting crimes combine volume, quality, diversity of variables, and adequate temporal coverage, which enables the replication of successful studies and advances in the accuracy of crime prediction across different contexts.

Table 7. Techniques for model performance.

Techniques	Authors
Hyperparameter tuning	[16,29,30,36,40,43,48,51]
Min-max normalization	[30,35,55]
Factorial Analysis of Mixed Data (FAMD)	[30,34]
Principal Component Analysis (PCA)	[30,31,34]
Multiple Correspondence Analysis (MCA)	[30]
Over-sampling − SMOTE	[30,40,51,76]
Under sampling	[40]
Data scaling	[40]
Shapley Additive exPlanation (SHAP)	[11,36,52,74]
Stacking (STK)	[38,59]
Adaptive pretraining	[57]
Adversarial training strategies and focal loss to balance imbalanced classes	[57]
Lasso regression	[73]

D. *RQ4. In what real-life context have machine learning based crime prediction models been implemented, and what have been the main challenges?*

Although machine learning models designed for crime prediction often show promising performance in scientific studies, the review of the selected articles suggests that most of these models do not transcend the academic field. Therefore, although the results achieved are useful, they are rarely implemented in real systems or integrated into operational applications for institutions such as police forces or government agencies. This phenomenon highlights a significant gap between theoretical research and applied practice, where models remain experimental and fail to have a tangible impact on decision-making or crime prevention in real-world contexts.

However, it is worth mentioning the effort made by Ref. [49], who created a dashboard using HTML, CSS, and JavaScript to display interactive graphics and other analyses in an organized manner. This

Table 8. Evaluation metrics.

Metrics	Frequency	Type Model	Maximum Performance	Optimal model	Articles
Accuracy	28	R/C	100.0 %	DeCXGBoost	[5,11,23,29,30,36,43,46,48,67,69,72–74]
Area Under the Curve (AUC)	4	C	99.4 %	XGBoost	[11,23,30,44,69,70,74,76]
F1-score	17	C	99.8 %	Hybrid model CNN-LSTM	[23,29,30,36,43,48,69,70,72,73,76]
Precision	12	C	89.8 %	DeCXGBoost	[11,23,29,36,43,44,48,51,69,72,73,76]
Recall	21	C	97.5 %	Support vector machine	[11,23,29,36,43,44,48,51,69,72,73,76]
Sensitivity	3	C	97.41 %	Hybrid Classifier (SVNN)	[5,11]
Specificity	3	C	98.1 %	Hybrid Classifier (SVNN)	[5,11,23]
Coefficient of determination (R^2)	9	R	89.0 % and 98.5 %	LSTM and GWRF	[16,35,47,66,67,72,75]
Mean Absolute Error (MAE)	8	R	0.008	Fusion model	[23,47,66,68,71,75]
Mean Squared Error (MSE)	3	R	0.93	Random forest regression	[35,66,71,75]
Root Mean Squared Error (RMSE)	7	R	0.145	ST-cokriging (Space-time cokriging)	[16,68,71–73,75]
Symmetric Mean Absolute Percentage Error (SMAPE)	2	R	0.2922	N-Beats (RNN-LSTM)	[16,35,47]
Loss	1	R	0.0511473	Federated LSTM	[71]

implies a clear intention and a further step to put these models in a real-world context. On the other hand [57], suggests integrating machine learning models in judicial assistance systems and smart courts. It is essential to clarify that the technologies and frameworks used include programming languages such as Java and Python, as well as the Scikit-learn library, along with RapidMiner Auto Model, among other tools [29–31,35,43,49].

Furthermore, the model was applied to a real-life case using daily data from Chicago's 22 police districts and proved useful in supporting operational decisions such as patrolling, resource allocation, and police investigation. However, no mention is made of direct practical implementation by a functioning police institution [68]. Also, the proposed algorithm is applied in a real-time multi-drone patrol context to respond to predicted crimes, assisting in patrol planning and response to high-risk areas [76].

3.1. Main findings

The systematic review identified that the most widely used models in crime prediction are XGBoost and Random Forest, due to their high performance in classification and regression. Additionally, the increasing use of deep learning models, such as LSTM and DNN, is also noted, particularly in hybrid approaches. Additionally, an emerging trend is the application of reinforcement learning, which enables dynamic adaptation to changing crime patterns. In terms of evaluation, the most widely used metrics include accuracy, AUC, F1-score, precision, and recall in classification, and R^2, MAE, MSE, and RMSE in regression, with complementary metrics such as PAI, PEI, and PCC in specific studies.

The most relevant variables for prediction include the date and time of the crime, geographic location (latitude and longitude), as well as contextual factors such as climate and temperature, highlighting the importance of broad temporal data in detecting historical patterns. Among the main gaps identified are the lack of standardization in metrics and variables, the need to integrate heterogeneous data sources, and the limited interpretability of advanced models. Future research is recommended to explore more explanatory hybrid models, optimize spatial data, and implement reinforcement learning techniques to enhance adaptability and accuracy in dynamic environments. Deployment architectures and integration of these machine learning models should also be considered.

Despite the promising results obtained in experimental settings, evaluating these models in real-world scenarios poses significant challenges. Many studies highlight issues such as data imbalance, missing records, and limited access to high-quality institutional datasets, which hinder consistent validation. Furthermore, the lack of standardization in metrics and input variables across studies complicates direct comparisons and real-life applicability. These factors underscore the need for robust, context-aware evaluation methods that account for operational constraints and local variability in crime reporting and data collection.

3.2. Machine learning techniques

Machine learning techniques enhance the accuracy of crime prediction through several strategic approaches. The integration of diverse data sources—such as historical crime records, geospatial variables,

Table 9. Data features/dataset origin.

City	Origin	Type of Crime	Features	Volume	Articles
Malaysia	Police	Theft, robbery	Location, year, month, temperature, and humidity.	–	[16]
Ethiopia	Police	Multiple	The age of the offender, the education status, the job, the victim's sex, the age of the victim, and the place	1600	[29]
Turkey	Police	Robbery	Location of each crime, age, and sex of the offender	2236	[35]
United Kingdom	Police and twitter	Diverse crime type	Crime type, location, date, latitude, longitude	–	[11]
Chicago	Open data	Violent crimes, property, drugs, theft, and assault	Type of crime, location (longitude, latitude), community area, and time of crime. Day of the week, holiday.	7 million 404269	[51,68]
Ukraine	Criminal records	Recidivism/Reoffending	Age at first conviction, number of actual convictions, number of suspended sentences, number of early dismissals	12000	[44]
Daegu	Metropolitan city	Urban crimes	Crime location, Bus stop, Closed-circuit television (CCTV), Police substation, Point of interest, Land cover area with detailed classifications, Statistical data, Floating population, and Card sales	373387	[36]
India	Diverse, Kaggle, NCRB	Multiple	They include demographic, economic, social, victim, and geographic variables. Rape, kidnapping, dowry deaths, sexual harassment.	+500	[46,72]
San Francisco	Kaggle	Criminal reports	Dates, Category, Descript, Day Of Week, Pd District, Resolution, Address, Longitude, Latitude	878049	[43]
Boston	Police	Uniform crime	District, reporting area, if shots were fired, date of the incident, day of the week, UCR category, and street	328000; 319073	[31,71]
Dallas	Open data	Robbery	Density and proximity to points of interest such as shops, public transport stations, hospitals, and parks	240481	[37]
Nigeria	News	Multiple	Type of crime, location, latitude and longitude, number of people killed, number of people kidnapped, property destroyed, arrests made, date of incident	–	[39]
City H	Public security office	Robbery	Business locations, time, weather conditions, stolen items, and case category	3629	[61]
Chicago, San Francisco, Ireland	Police	Assault, burglary, theft, robbery	Primary type, local description, district, FBI code, among others.	–	[32]
California	Police	Theft, vandalism, possession of weapons	Date and time, crime category, location, record identifiers	272333	[58]
Los Angeles	Open data	Multiple	ID, date, type of crime, description, location (latitude and longitude), year, zip code, and police district	2646463	[33]
India	National crime records bureau	Murder, rape, robbery	Date, type of crime, location, number of cases, among others	1860	[59]
Nueva York and Israel	NYC open data	Serious assaults	Age, gender, income, poverty rates, educational levels, and presence of recreational facilities. Historical thefts, weather conditions	–	[42,70]
City ZG	City	Theft, robbery	Population at risk, Physical street environment, Social disorganization, Number of bars, internet cafes, supermarkets, subway stations, bus stops, and ATMs, wealth index	–	[66,74]
Bahréin	Police	Theft, assault, and vandalism	Age, gender, occupation, nationality, marital status, type of crime, location, date, and time of the crime.	720	[67]
Portugal	Police	Multiple	Date, time, type of crime, parish, and street where the crime occurred.	42000	[73]
Peru	INEI	Robbery, theft	Location: District, presumed place of occurrence, latitude, and longitude. Time: Year, month, day, hour, and minute of the crime. Type of crime: Robbery, theft, aggravated robbery, among others.	490916	[75]
Denver	Public data	Multiple	Crime identifiers, dates of occurrence, geographic location (latitude and longitude), type of crime, and its location	546882	[76]

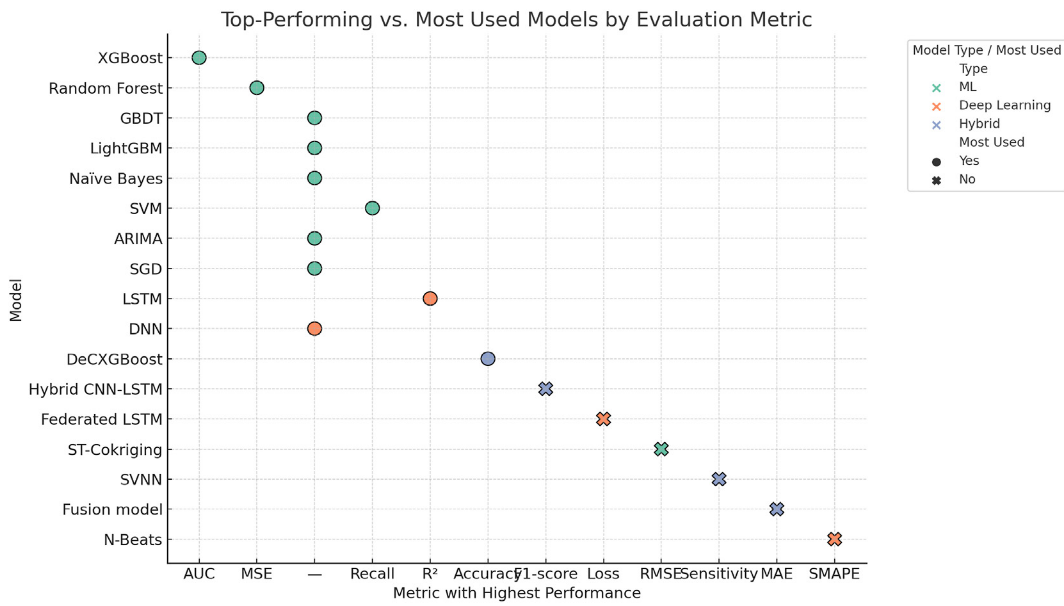

Fig. 3. Top-performing models by metric and type.

weather conditions, and social media—enriches datasets and enhances model performance [23,47,62]. Algorithms like XGBoost, Random Forest, LSTM, and DNN are particularly effective in identifying hidden patterns and capturing non-linear relationships among variables.

Moreover, real-time data processing enabled by scalable architectures and frameworks—such as Machine Learning Operations (MLOps) [63,64]—allows for continuous model updates and deployment. This adaptability ensures that predictions remain responsive to the evolving dynamics of crime. Reinforcement learning further supports adaptive learning by enabling models to adjust to new patterns without constant manual retraining. Advanced feature selection and engineering techniques, including dimensionality reduction and spatial embeddings, improve data representation and model interpretability. Collectively, these strategies enhance the precision and practicality of crime prediction models, offering valuable tools for public safety decision-making [48].

3.3. About the bibliometric analysis

The bibliometric analysis was performed using Vos Viewer and R software, along with its Bibliometrix and Biblioshiny libraries, which have proven effective in these studies. The search string obtained 530 articles related to the research topic.

Fig. 4 shows the co-occurrence of key terms in the scientific literature, grouping them into five thematic clusters: (i) traditional machine learning techniques (decision trees, random forest, XGBoost) for crime prediction; (ii) deep learning models (convolutional neural networks, computer vision) in crime detection; (iii) classification and feature extraction approaches in data mining; (iv) predictive analysis and spatial analytics in smart cities and law enforcement; and (v) hybrid methodologies and emerging techniques (contrastive learning, artificial neural networks). This representation highlights current trends and identifies key areas for future contributions in crime analysis.

On the other hand, Fig. 5 illustrates the temporal evolution of key topics. Terms in blue, such as data mining and crime detection, represent the foundational aspects of the field. In contrast, terms in yellow, including XGBoost, LSTM, and reinforcement learning, indicate emerging areas of recent interest.

Fig. 6 shows that different countries are interested in researching the topic addressed in this review.

3.4. About the selection

After the article selection process, 50 were obtained for in-depth review. These copies come from different years of publication and different quartiles. Fig. 7 shows the growing trend of the study topic. Fig. 8 illustrates the number of articles selected according to their quartiles, providing a more precise measure of the research quality and relevance, with 46% falling into Q1.

3.5. Proposal model

Although crime prediction models have demonstrated high accuracy in experimental settings, their

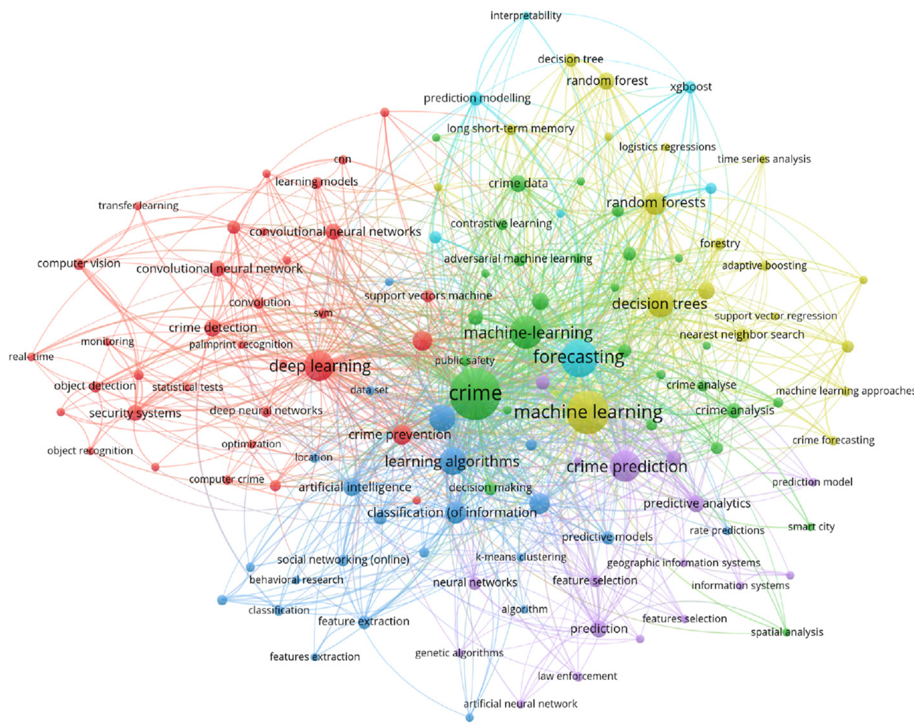

Fig. 4. Network visualization.

real-world impact depends on successful integration into institutional systems. These models offer valuable potential for optimizing the allocation of police resources by forecasting high-risk areas and periods [77]. However, without mechanisms for explainability and continuous adaptation, their practical utility may diminish over time [78]. These studies highlight the importance of integrating predictive models into public safety frameworks in a dynamic and sustained manner.

Despite significant advances in crime prediction through deep learning, a critical gap remains between experimental success and real-world implementation. While Shan *et al.* [79] report high

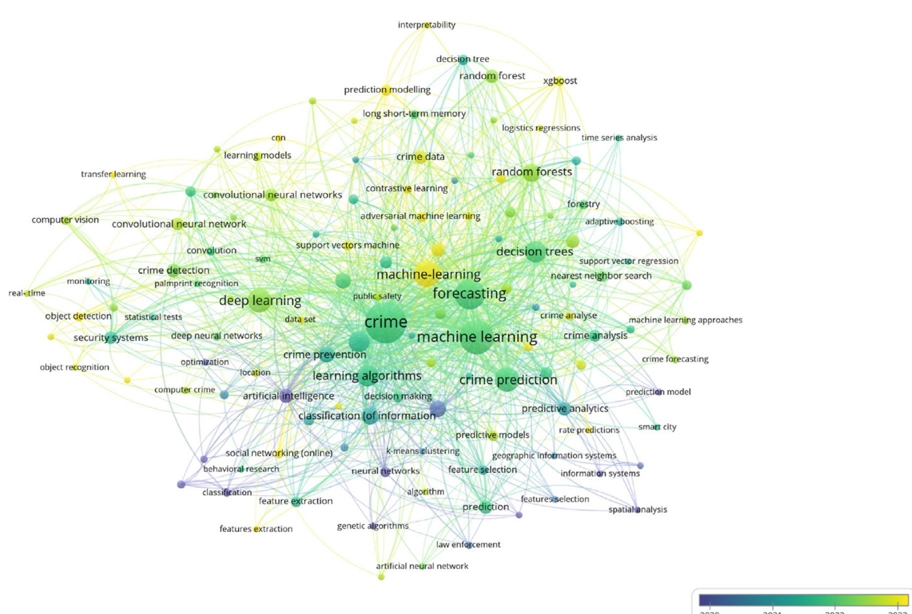

Fig. 5. Overlay visualization.

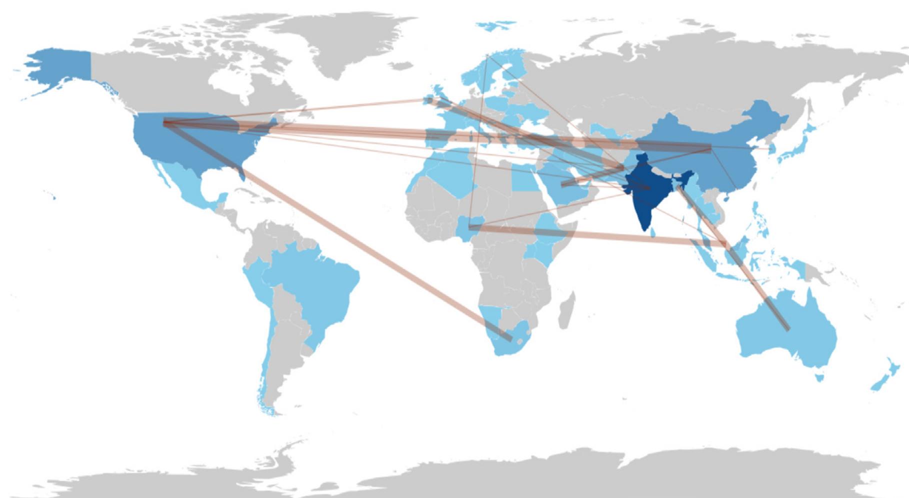

Fig. 6. Country collaborations maps.

predictive accuracy in datasets from New York, Chicago, and CN-County, they acknowledge the challenge of generalizing to noisy and dynamic urban environments beyond controlled settings. Likewise, Gerards and Hashemighouchani [80] emphasize that most AI-based crime prediction systems remain within academic boundaries, urging the need to overcome the research-to-practice divide. Both studies agree that bridging this gap requires not only robust models but also their integration into operational law enforcement systems to ensure real-world impact and reliability.

As a synthesis of the study's findings, architecture for developing and deploying machine learning models for crime prediction is proposed (See Fig. 9). The first phase involves understanding the data. This implies understanding the business to comprehend the database, including its tables and columns, particularly when working directly with the source of information. If the research is conducted using provided datasets, it is essential to ensure and guarantee a thorough understanding of each dataset attribute directly with the individuals who provide this input. The second phase involves data preprocessing, which includes data cleaning, removing duplicates, handling outliers, selecting relevant attributes, and transforming data as necessary [8,64].

The third phase involves modeling, which includes the feature engineering sub-phase, where techniques such as data scaling, principal component analysis (PCA), data regularization, and class balancing may be applied. During the model training sub-phase, the algorithms identified in this review are utilized. This is followed by the evaluation sub-phase, where model performance is assessed using the metrics outlined in the study. If the results do not meet performance expectations, the training cycle is repeated with hyperparameter tuning until satisfactory accuracy is achieved. The fourth phase focuses on deployment, where the selected model is brought into production. This

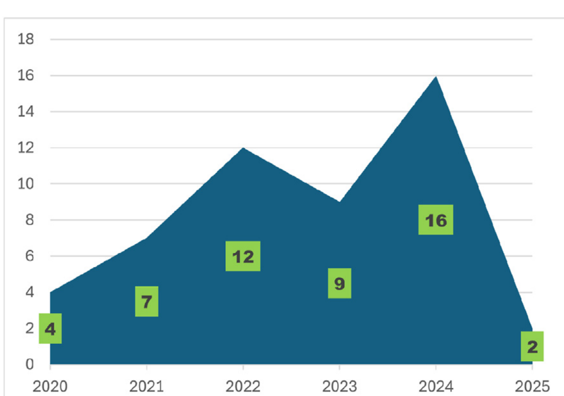

Fig. 7. Selected articles by years.

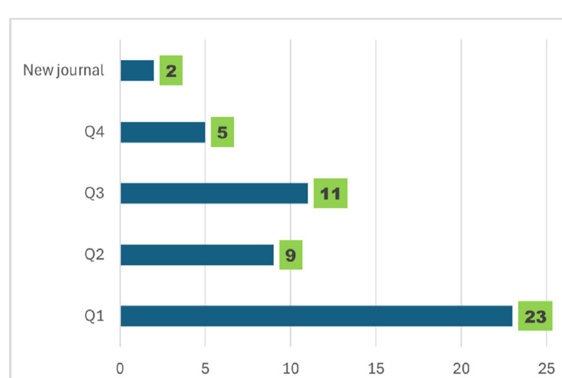

Fig. 8. Selected articles by quartiles.

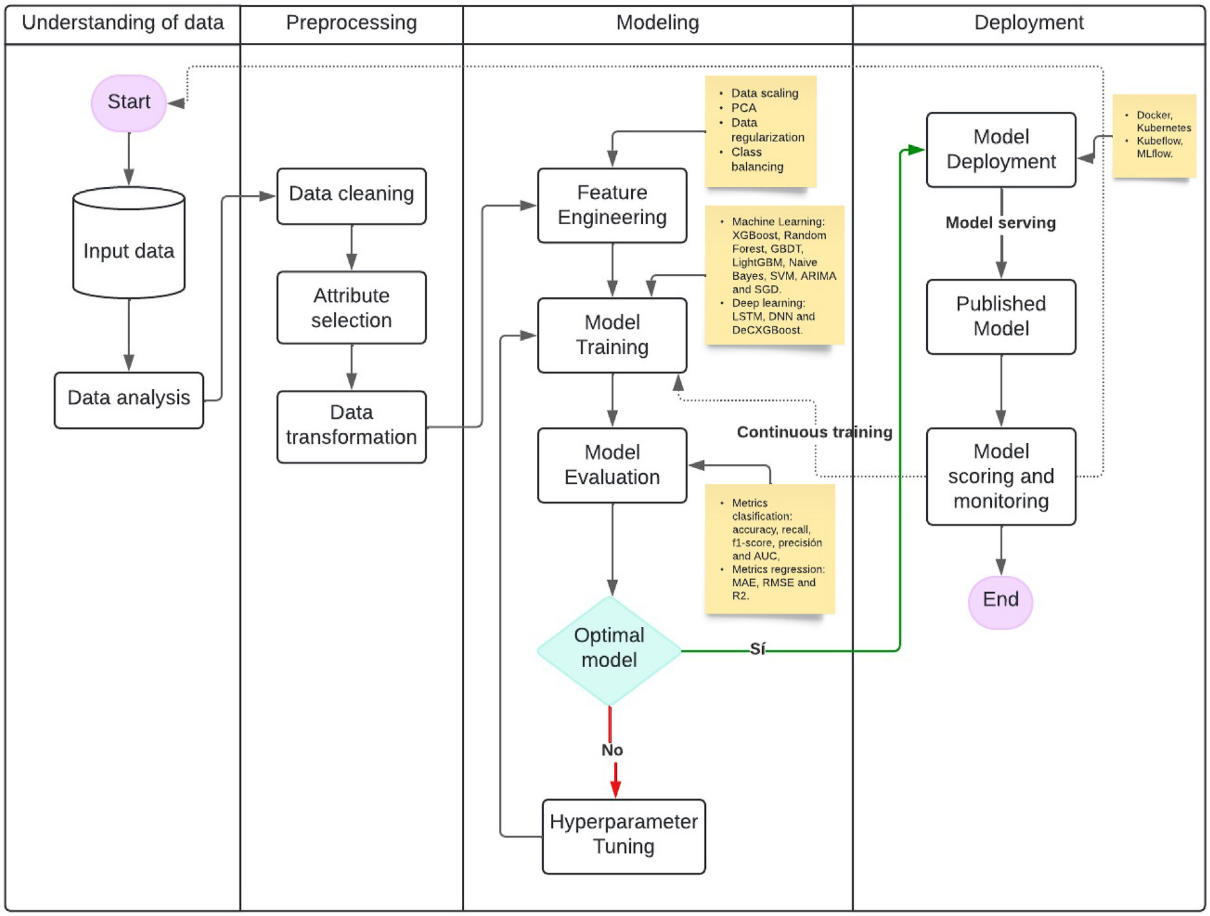

Fig. 9. Proposed model.

stage must include performance monitoring to automatically verify whether the model maintains efficiency or begins to degrade. To address this, a continuous training pipeline should be implemented to automate the retraining process and maintain performance over time [8,43,63,64].

The integration of MLOps (Machine Learning Operations) into crime prediction and detection systems represents a significant advancement in automating and optimizing the continuous deployment of models. This study proposes a systematic framework that spans from data acquisition and preprocessing to model development, training, deployment, and monitoring, ensuring adaptability to evolving crime patterns. One of the key challenges lies in automating monitoring and retraining processes—an area where MLOps plays a pivotal role by supporting scalability, reproducibility, and sustained model maintenance. Ultimately, this phase highlights the significance of addressing ethical considerations, ensuring transparency, fairness, and data privacy in the deployment of machine learning technologies within the public safety domain [63,64].

The use of MLOps in machine learning is essential, as it enables the structured and automated management of the entire model lifecycle—from data analysis to deployment in production. Technologies such as Jupyter Notebook, Python, Docker, and Heroku facilitate continuous integration, reproducibility, and model monitoring, which enhances operational efficiency, reduces manual errors, and ensures ongoing adaptation to new data or changes in the environment [65].

At this point, we must find a way to integrate MLOps to facilitate the efficient and scalable management and operation of machine learning models in production. This proposal could be applied to other areas of study.

Implementing machine learning and MLOps in crime prevention faces key challenges. Data quality and availability remain a hurdle, as many datasets are incomplete or biased. Integration with existing systems is complex due to outdated infrastructures, requiring interoperable solutions. Trust in models depends on their accuracy and consistent performance, which requires continuous monitoring and tuning. There are ethical and legal risks, including privacy concerns and algorithmic bias, that necessitate clear regulations to address. Lack of resources can be mitigated with MLOps and cloud computing, optimizing costs and scalability. Continuous evaluation is essential for adapting models to the changing nature of crime, as crime is not random but follows spatial and temporal patterns. Models that combine static data, such as demographic characteristics, with dynamic sources, such as urban mobility records (taxi data), have been shown to improve accuracy in crime prediction [63−65]. Furthermore, public acceptance depends on communication and transparency strategies. Overcoming these challenges requires technological innovation, effective regulation, and inter-agency collaboration.

3.6. Discussion

This review highlights the growing study of machine learning models in crime prediction, focusing on classification models, while regression models are comparatively less explored. In the first instance, this leaves a gap for further study of regression models [33,47,58]. While it is true that the purpose of this review was to identify the most commonly used machine learning models, it was also found that deep learning models were often used in conjunction, yielding interesting results, as shown in Tables 5 and 6. This suggests that combining multiple models and techniques is necessary to achieve high-performing and effective solutions [45,55−57].

The studies and metrics found reveal that it is insufficient to use only one or two metrics to evaluate a model's performance. In these studies and also in other areas, it is recommended to use all the metrics in Table 8, depending on the type of research purpose and the model, whether it is classification –if it is desired to predict discrete labels or categories– or regression –if it is desired to predict continuous numerical values–, also taking into account the other metrics indicated in the answer to question RQ2.

To achieve both high performance and precision in a model, the data quality, the number of records, and the characteristics or variables to be considered in the dataset are significant. In this sense, regression type prediction models consider date and time variables; from these variables, the year and month can be extracted if they are not available [58]. Regarding location, it is advisable to include coordinates to improve location precision [34]. Likewise, variables outside of crime records should be integrated to include climatic data [16,53]. At this point, it is recommended to have detailed knowledge of the data source, specifically understanding the variables in each dataset. It is crucial to understand the context and purpose behind data collection by institutions, such as police departments or justice agencies.

All the reviewed articles recommend applying the proposed models in institutions such as police departments and justice agencies. However, there is little to evidence of real-world implementation or practical applications reaching end-users. This reflects the main gap identified by the review: the transition from experimental models to operational deployment. Achieving this requires not only technical robustness but also institutional alignment, ethical oversight, and contextual understanding of data systems. In real settings, significant challenges arise, including inconsistent data quality, missing values, and the fragmentation of datasets generated under evolving administrative processes. Furthermore, a limited understanding of the operational logic within justice institutions can hinder the alignment between algorithmic outputs and institutional workflows. Bridging this gap demands interdisciplinary efforts to validate, adapt, and deploy these models under real-world constraints, supported by strong collaboration between researchers and institutional stakeholders.

4. Conclusions

In this systematic literature review, conducted using the PRISMA methodology, the 4 research questions posed were answered after reviewing and analyzing the 50 selected articles. Regarding the first question about which machine learning models are most used and which are most effective for predicting crimes, this study found that various models are being employed. Still, the most notable are XGBoost, random forest, gradient boosting decision tree, LightGBM, Naive Bayes, support vector machine, ARIMA, and stochastic gradient descent; likewise, deep learning models such as LSTM, DNN, and DeCXGBoost also stand out, and hybrid models are also present, as seen in Table 5.

Regarding the second question, which metrics are used to evaluate the performance of machine learning models, it was found that accuracy, recall, f1-score, precision, and AUC are the most used and determining when evaluating classification models; on the other hand, metrics such as MAE, RMSE and R^2 are the most determining in regression models.

Regarding the third question, which characteristics are relevant in the dataset for greater precision in the models, it was found that most of the datasets include types of crimes, date and time, month, year, age, gender, educational level, both of the offender as well as the victim, it was also found that a large part of the studies are oriented to the determination of the area, which is why they include data on latitude and longitude (geographic coordinates) and other interesting characteristics are the inclusion of climatic data, temperature, humidity and concurrent areas.

Finally, regarding the implementation of the models in a real context, surprisingly, no study was found that after obtaining the most efficient model, it was implemented in a real context or at least included in some public facing application, except one that implemented a series of dashboards to display heat maps on a web page. This type of result is important in demonstrating how they are integrated, what results can be achieved for end users, and providing information for informed decision-making within the corresponding organizations. There is a clear gap between academic research and its implementation in real-world contexts.

Future research should address the current challenges and limitations identified in this study. A key challenge is the need to improve regression models, which can be optimized by integrating reinforcement learning techniques and optimizing the evaluation metrics used in crime prediction. Furthermore, data availability and quality remain critical issues. To improve prediction accuracy and model robustness, future studies should focus on expanding datasets by incorporating external factors beyond crime records, such as socioeconomic indicators, geospatial analysis, real-time surveillance data, behavioral trends, and the status of court cases, as essential indicators for prediction that assist law enforcement agencies.

Another critical challenge is the practical implementation of predictive models. Future work should not only develop more accurate models but also explore how to integrate these solutions into law enforcement operational systems. This includes designing scalable implementation architectures, creating intuitive visualization tools, and developing prototypes that demonstrate real-world applicability. Furthermore, collaboration with law enforcement agencies and local governments is essential to ensure alignment with institutional processes, foster trust in predictive systems, and facilitate access to real data for validation. By providing structured guidelines, implementation roadmaps, and evidence from pilot programs, future research can effectively bridge the gap between theoretical advances and practical adoption in justice and public safety contexts.

Ethics information

The study did not involve humans or animals, so ethical approval was not required under current regulations.

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Conflict of interest

The authors declare no conflict of interest.

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