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Review Article

Artificial intelligence & crime prediction: A systematic literature review

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ABSTRACT

The security of a community is its topmost priority; hence, governments must take proper actions to reduce the crime rate. Consequently, the application of artificial intelligence (AI) in crime prediction is a significant and well-researched area. This study investigates AI strategies in crime prediction. We conduct a systematic literature review (SLR). Our review evaluates the models from numerous points of view, including the crime analysis type, crimes studied, prediction technique, performance metrics and evaluations, strengths and weaknesses of the proposed method, and limitations and future directions. We review 120 research papers published between 2008 and 2021 that cover AI approaches for crime prediction. We provide 34 crime categories researched by researchers and 23 distinct crime analysis methodologies after analyzing the selected research articles. On the other hand, we identify 64 different machine learning (ML) techniques for crime prediction. In addition, we observe that the most applied approach in crime prediction is the supervised learning approach. Furthermore, we discuss the evaluation and performance metrics, as well as the tools utilized in building the models and their strengths and weaknesses. Crime prediction AI techniques are a promising field of study, and there are several ML models that researchers have applied. Consequently, based upon this review, we provide advice and guidance for researchers working in this area of study.

1. Introduction

The safety of a community is its top priority, and as a result, governments take necessary actions to reduce crime rates. This, in turn, ensures economic growth and quality of life. Crime analysis is a critical part of criminology that focuses on studying behavioral patterns and tries to identify the indicators of such events (Mahmud et al., 2017). However, several complications arise during crime prevention efforts. This is due to the variety of crime types, motives, repercussions, handling methods, and prevention techniques. Due to these complications and various attributes, crime prediction has become a powerful and widely used technique. As a result, police departments spend a great deal of time and resources detecting crime trends and predicting them. With the growing shift toward technology and advancements in artificial intelligence (AI), Machine Learning (ML) techniques could reduce this effort by quickly analyzing large amounts of data to extract crime patterns (Feng et al., 2018). Several AI techniques have been widely studied to reduce or prevent crime and ensure the safety of people in different countries. Going forward, these machine learning models can be used in predicting future crimes, their attributes, etc. Machine learning will enable police departments to optimize their resources by finding hotspots based on time, type, or any other factor (Bellarmine, 2018). Moreover, analyzing crime records could reveal more information about the social structure of communities. Hence, government entities and decision-makers will be able to better know which age ranges, nationalities, etc. to focus on in order to prevent related problems.

Attempting to predict crime manually would be difficult, and as such, machine learning techniques are now being widely utilized to aid in crime prediction and prevention. Traditionally, a technique called "hotspot analysis" has been used by police departments to prevent crimes (Butt et al., 2020; Eck et al., 2005; Kouziokas, 2017a; Umair et al., 2020). In this approach, previous offense and crime data are simply uploaded into an overlay on a map, which allows officers to deploy more resources into these areas. However, this strategy is not predictive; rather, it is a reaction to what has happened in the past.

By contrast, AI techniques could be useful in analyzing the datasets collected by police departments to extract patterns and predict future events. As an example, (Kim et al., 2019a), used such a dataset to examine crime data from Vancouver over the last 15 years. They used a heatmap to predict the areas most likely to experience crime, i.e., hotspots, and used different AI approaches, including boosted decision trees with K-nearest neighbors.

Through ML and AI, new methods and approaches are available to lead and aid the process of crime prediction. In this context, crime

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prediction refers to the use of mathematics and law enforcement, and predictive analytics is used to forecast probable and potentially criminal activities in a specific area. This predictive analysis is based on specific attributes of crimes that have occurred in certain areas. These attributes are vast and may vary over time depending on certain variables such as the type of crime, crime location, and crime trends. Crime is a broad term and as such, it can be categorized into different forms (Borowik et al., 2019). This includes property crimes (burglary, theft, and shoplifting), violent crimes (homicide, kidnapping, and sexual assault), and so on. Crime frequency can vary depending on the time of day, day of the week, and even time of year (Borowik et al., 2019). Geographic location also plays a large role, as there are both high-risk and low-risk areas regarding crime occurrence (Toppireddy et al., 2018; Yao et al., 2020). Currently, these different factors are considered when distributing police forces across areas. cause these and many other attributes have a large variety of different values, ML is the ideal data analysis method to tackle this problem. The application of AI in crime prediction is a real-life application that being made possible because AI researchers are prioritizing the importance of building interpretable and transparent models (Vinuesa & Sirmacek, 2021).

Attributes in crime datasets can focus on two different attributes: location-based attributes of where the crime occurred and neighborhood information, such as the unemployment rate, household income, population, etc. (Mittal et al., 2019). Other datasets contain attributes related to the crime itself, crime type, day of the week, weapon used, victim information, etc. (Bellarmine, 2018). There are even some datasets that combine both crime and neighborhood data.

In this study, we provide an extensive systematic literature review to understand the research attempts and trends in crime analysis and prediction. Specifically, we focus on how research papers that use neural networks, ML, and deep learning techniques leverage their capabilities in predicting crime trends and occurrence probability. Moreover, our project aims to study research endeavors in predicting the location and time of a crime, as this can help optimize police department efforts and resources.

The research was done methodically, and articles were selected concerning (i) the primary crime prediction research work conducted, (ii) the techniques utilized in crime prediction, (iii) the estimation and performance metrics of the proposed models, and (iv) the limitations and strengths of the proposed models.

The rest of the paper is split into five parts. The literature review is provided in Section 2. In Section 3, an outline of the approach methodology of this research is presented. The outcomes and results of this review are discussed in Section 4. Section 5 includes the conclusions and recommendations for future work.

2. Literature review

The type of methods and the purpose behind the different crime prediction studies and applications varied in the papers we collected. Many of the crime prediction methods were developed for generic crimes and situations, where different models were used and tested in crime prediction to determine the most effective one relative to the provided dataset. For example, in (Kim et al., 2019a), an investigation was conducted using ML to predict generic crime. However, some methods have been developed for particular crime types or categories, such as in (Srivastava et al., 2008), who modeled the credit card transaction sequence of operations using a hidden Markov model (HMM). Other papers have focused on performing a comparative analysis between the different learning model types, such as (Babakura et al., 2015), where two classification algorithms, namely, naïve Bayes and backpropagation, were compared for predicting the crime category based on a given dataset. Their experiment was performed using 10-fold cross-validation, and the findings show that naïve Bayes performed better than backpropagation for their crime dataset using Weka. Moreover, a few of the papers also stood out in regard to their objectives. For example, (Nasridinov et al., 2013), worked with different learning models and algorithms and tested them with different datasets. They concluded that it is critical to select a model type based on the dataset provided, as certain datasets are more compatible with different model types.

On the other hand, some recent surveys have explored crime prediction methods. For example, (P. Saravanan et al., 2021), provided a survey that explores data mining methods for crime prediction based on different crime prediction factors, such as socioeconomic, spatial-temporal, demographic, and geographic attributes. Furthermore, a systematic literature review was provided by (Butt et al., 2020) in which the authors present their contribution to the detection and prediction of spatiotemporal crime hotspots. They provided the approaches of ML and data mining in hotspot detection, in addition to their effectiveness, and outlined the challenges of building a spatiotemporal crime prediction model. Separately, (Kawthalkar et al., 2020), reviewed the various technological mapping solutions for crime prediction in smart cities. The authors took into account several different representations of criminal depictions and conducted a comparative study. The authors believe that many ideas and procedures have been established for crime prediction, but that field testing is necessary for the usability of those approaches. In addition, in (Albo, n.d.), the authors focus on artificial neural networks and convolutional network techniques for forecasting crimes.

Safety and security are key important aspects that improve the quality of life in urban areas. The authors (Zhao & Tang, 2018) presented an overview that summarized crime analysis in urban data, studied several types of criminal task algorithms, and discussed theories on criminology. Additionally, (Shamsuddin et al., 2017), provided a short, straightforward survey on the implementation of methods for crime prediction and the chances of improving them in the future. They used SVM, fuzzy theory, artificial neural networks, and multivariate time series as ML methods. On the other hand, (Fredrick David KR et al., 2017), presented a review of the supervised and unsupervised strategies for crime detection in which they analyzed and forecasted crimes.

We present a systematic review study on AI strategies for crime prediction, which differs from existing work in this literature. Table 1 presents a small summary of other surveys and the difference between their contributions and ours. Our research differs from previous research in a number of ways, including the following:

1. Presents the main focus of research in crime prediction with respect to the type and category of the crime, the study time, and which type of crime has been addressed by the most researchers.
2. Clarifies the frequency of what algorithms were used in training models and what factors were considered when choosing them.
3. Analyzes the estimation accuracy of the models by focusing on four factors: performance metric, evaluation value, the dataset utilized, and the validation approaches for the model.
4. Demonstrates the tools applied in the selected research papers, the strengths and weaknesses of the prediction models, and the limitations and future direction of crime prediction.
5. Covers the period from 2008 to 2021, which addresses recent work.

3. Methodology

In this study, we used the systematic literature review (SLR) technique provided by (Kitchenham & Charters, 2007) to create a survey. It is divided into three phases: planning, conducting, and reporting, each of which comprises multiple stages. We provide a review methodology that contains six stages: defining research objectives, developing the search strategy, identifying study selection processes, establishing quality evaluation guidelines, outlining the data extraction technique, and synthesizing the acquired data during the planning phase.

To specify our research questions, we first set our objectives and revolved our research questions around them. The search strategy was

Table 1
Related work summary.

Survey	Year	Summary	Difference
Mookiah et al. (2015)	2015	Discusses research that takes into account crime-related variables and demonstrates how, in certain circumstances, information that is often assumed to influence the crime rate does not.	Research in this survey aims to prove that some variables that are thought to affect the crime rate do not, whereas in our survey the research aims to study the prediction research on crimes and what algorithms are used, along with their accuracy.
Thongsatapornwatana (2016)	2016	Reviews work on various data mining applications used to solve crimes to help beginners in data mining research.	This survey focuses on the data mining techniques and their results alone, while our survey puts equal focus on all parts of the collected research.
Fredrick David and Suruliandi (2017)	2017	This study explores crime analysis and prediction utilizing a variety of data mining approaches.	This study is similar to our work; however, it restricts its research to only supervised and unsupervised learning, whereas in our survey there are no such restrictions.
Grover et al. (2007)	2007	In this review, the authors categorize the techniques of crime prediction into three main types: statistical methods, geographical methods, and pattern analysis with ML methods.	This survey is similar to our paper in identifying the techniques; however, our paper provides more detailed and rich knowledge about the techniques. In addition to our survey studying crime prediction from several perspectives (not only the techniques), we also provide information about the type and analysis of crimes, the estimation and evaluation metrics, and the strengths and limitations of those techniques.
Dubey and Kumar Chaturvedi (2014)	2014	This survey presents a comparative review of the detection and prediction strategies for crime with data mining techniques.	This survey presents the data mining techniques used in crime prediction. Nevertheless, our survey studies a wider range of papers and covers more recent techniques and methods in this field.

defined as choosing the appropriate search terms that, when used, would result in finding the related articles required to conduct our research. Fig. 1 illustrates the research methodology applied in this review.

3.1. Research questions

Our objective is to study the prediction research work on crimes using AI. The objective is achieved through answering four main research questions. They covered the type and category of the crimes considered. The main ML algorithms that are used to predict crimes in relation to how accurate they are and determining what makes a certain training model suitable with the data provided. In addition to the strengths and limitations of the algorithms.

1. RQ1: What is the primary focus of crime prediction work?
   RQ1 aims to present the main focus of research in crime prediction with respect to the type and category of crime, the study time, and which type of crime has been addressed by the most researchers.
2. RQ2: What ML algorithms are used in crime prediction?
   RQ2 aims to clarify the frequency with which different algorithms were used in training models and what factors were considered when choosing them.
3. RQ3: What are the performance metrics for the ML applied?
   RQ3 would allow us to properly analyze the estimation accuracy of the models used by focusing on four factors: performance metrics, evaluation values, the dataset utilized, and validation approaches for the model.
4. RQ4: What are the tools utilized in the approach? What are the strengths and limitations of the proposed approach?
   RQ4 aims to identify the tools applied in the selected research papers, the strengths and weaknesses of the prediction models, and the limitations and future direction of crime prediction.

3.2. Search strategy

Below is a comprehensive explanation of this review's search strategy.

The construction of our search terms was defined by using the following procedures:

1. Key search phrases derived from the research goals and questions were identified.
2. New phrases were decided upon to replace the key ones.
3. To filter unnecessary search results, Boolean operators were used (ANDS and ORS).

The search terms used were related to crime prediction and ML techniques, which include the following: ("crime prediction" OR "crime analysis") AND ("artificial intelligence" OR "machine learning OR "deep learning" OR "data mining'' OR "pattern recognition'' OR "nearest neighbor'' OR "regression tree'' OR "decision tree'' OR "classification tree'' OR "neural network'' OR "genetic algorithm'' OR "genetic programming'' OR "association rule'' OR "Bayesian net'' OR "Bayesian belief network'' OR "support vector regression'' OR "support vector machine'')

The following digital libraries were used to find the relevant research papers:

- Google Scholar and Scopus
- Springer
- IEEE Explorer
- ACM Digital Library
- Elsevier

After applying our inclusion and exclusion criteria, we ended up with a total of 120 papers, 50 and 70 of which were journal studies and conference articles, respectively.

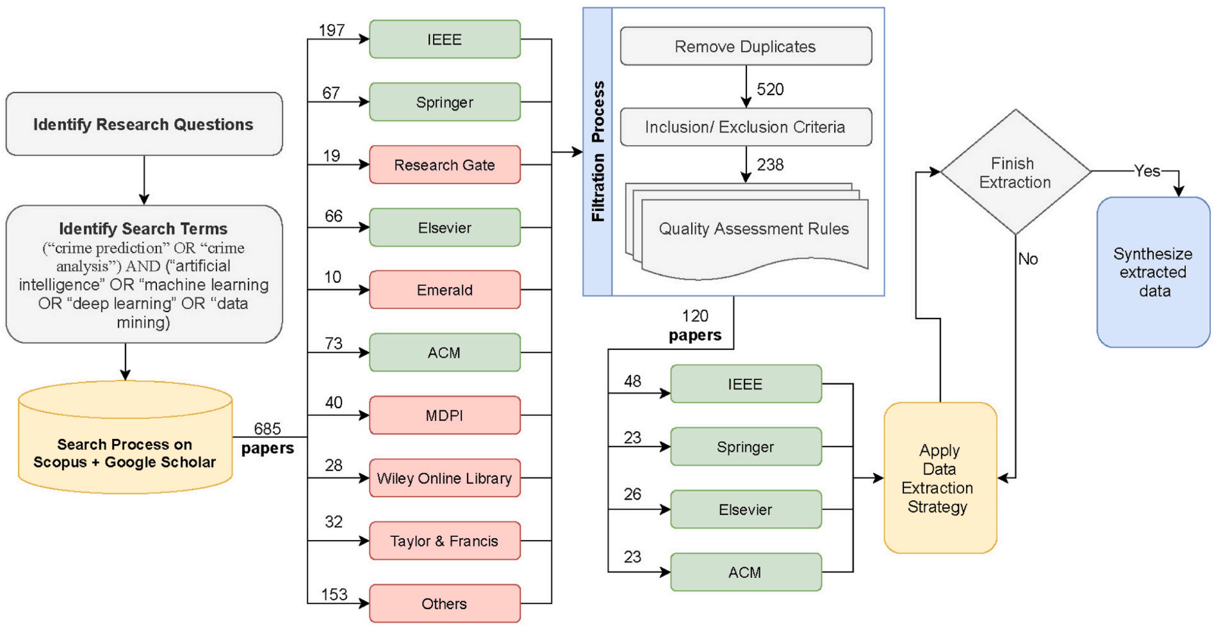

Fig. 1. Applied research methodology.

3.3. *Study selection*

The initial list of papers obtained consisted of approximately 350 papers using the search terms. However, after filtering those papers to confirm that only those that were related to our research remained, we ended up with a total of 120 papers. The filtration and selection process is discussed as follows:

1. Eliminate duplicates of articles obtained from different libraries and authors.
2. Remove irrelevant articles and preserve those that met the inclusion criteria by using the inclusion and exclusion criteria.
3. Include articles that comply with the quality assessment rules to ensure that high-quality papers remain.

4. Continue searching for related articles and apply step 3 to these additional articles

The criteria followed during the inclusion and exclusion phase are as follows Table 2:

4.1. *Quality assessment rules (QARs)*

Finally, QARs were used to assess the acceptability of the articles acquired in response to the study questions. Ten QARs were established, with each rule receiving one point out of ten. The score was determined as follows: "fully answered" = 1, "above average" = 0.75, "average" = 0.5, "below average" = 0.25, "not answered" = 0. The score of the article is the sum of the points earned from all ten QARs. An article was considered if the result was 5 or greater; otherwise, it was excluded.

1. Is the research purpose well defined?
2. Is the ML background described properly?
3. Are the ML algorithms employed well defined?
4. Is the experiment's design appropriate and acceptable?
5. Is the study based on adequate crime data?
6. Is the provided ML methodology reviewed with other techniques?
7. Are the experiment's outcomes properly stated and reported?
8. Are the evaluation metrics of the proposed methods appropriate?
9. Is the evaluation metric compared to other methods?
10. In general, does the study benefit the academic or industrial communities?

Table 2
Exclusion and inclusion criteria.

Exclusion criteria	Inclusion criteria
• Articles about ML that are not related to crime prediction are excluded. • Articles that do not employ ML to forecast crime should be excluded. • Exclude nonrefereed publications.	• Crime prediction through ML approaches. • Crime prediction utilizing data mining techniques. • Research comparing ML vs. non-ML methodologies. • Consider only articles published from 2008. • Include journals and conference papers only.

4.2. *Data extraction strategy*

The goal of this step was to conduct an analysis of the final list of publications to extract the information needed to answer our given research questions. The retrieved data produced the following results: reference, publisher, journal/conference, features, crime type, dataset, accuracy, model type, category, analysis type, software/tools, and paper summary.

4.3. *Synthesis of extracted data*

Different approaches were utilized to aggregate evidence that would answer the RQs to synthesize the extracted data from the selected articles. The following is a detailed description of the synthesis technique we used. The narrative synthesis method was utilized to extract information for RQ1 and RQ2, which was then tabulated. Binary outcomes were used to analyze the results of the information obtained from RQ3 and RQ4. It is essential to mention that not all studies have addressed the four research questions.

5. Results and discussion

This section discusses the findings of this analysis. This subsection provides an overview of the papers chosen for this review. The findings of each study topic are discussed in detail in the following four parts. As previously described, the study is based on the quality evaluation criterion scored by the selected studies. Research articles with a grade of 5 or better (out of 10) were considered. In addition, Table 7 in the Appendix mentions the frequency of the selected articles' QAR scores. The total number of studies selected was 120, which utilized AI methods such as data mining and ML for crime prediction. The research studies were published between 2008 and 2021. Table 11 in the Appendix provides the list of research papers.

5.1. Main focus of research in crime prediction

In this section, we present the findings of RQ1, which discusses the state of research in crime prediction with respect to the type and category of the crime, time of the study, and the kind of crime most researchers have been discussing.

Analysis of crimes can be performed in several ways. Table 3 presents the crime analysis types that were utilized in the selected papers. For simplicity, we categorized the types into 5 main aspects. Crime, spatial, human behavior analysis, social media, and others. Furthermore, some works in the literature have used the spatial aspect in analyzing crimes, for example, by performing spatial clustering, spatial correlation, studying hotspots, or even analyzing the demographics of census regions. Another approach to analysis is studying human behavior. This includes studying the criminal behavior, facial expression analysis, point of interest (POI) analysis, and analyzing activities. Social media was utilized for crime analysis in several research papers. In particular, Twitter was one of the main social media platforms utilized for crime analysis, and researchers are taking advantage of tweets that may refer to criminal actions.

According to Table 3, analyzing the crime density and neighborhood was the most used approach since 52 research papers utilized this approach, making up 43% of papers. The spatial analysis aspect was performed by 19 research papers, or 16% of all papers. A total of 9 research papers, or 7%, applied human behavior analysis for crime prediction. A total of 24 research papers did not specify their approach in analyzing the crimes (20%).

Table 3
Categorized crime analysis types.

General Category	Analysis type	Freq.	Percentage	Total
Crime	Neighborhood	13	43%	52
	Crime	32		
	Crime & Neighborhood	5		
	Crime density	2		
Spatial	Spatial clustering	3	16%	19
	Spatial correlation	7		
	Hot spot analysis	8		
	Census demographic analysis	2		
Human behavior analysis	Human behavior analysis	2	7%	9
	Criminal behavior analysis	1		
	Facial expression analysis	1		
	Activity analysis	1		
	POI interest	3		
	Surveillance	1		
Other analysis (convergence, qualitative, frequent pattern, feature selection)	Feature selection	3	8%	9
	Predictive policing	1		
	Qualitative	2		
	Convergence	1		
	Frequent pattern	2		
Social media	Object/image analysis	1	6%	7
	Tweets	3		
	Text	1		
	Social media	2		
Not applicable	NA	24	20%	24
Total				**120**

Fig. 2 demonstrates the distribution of crime analysis type by year within the time period under consideration. As demonstrated in the figure, in 2018, most of the research papers used crime density as an approach for predication analysis. However, in 2020, analyzing spatial data was the aspect that was the most common.

Several different types of crime exist. We list some of the main crimes and their definitions:

- **Robbery**: the act of unlawfully removing the property from a person or place through force or fear of force.
- **Burglary**: the act in which someone enters a building with the intent of stealing, injuring someone, or causing harm.
- **Theft**: taking something that belongs to someone else and holding it dishonestly.
- **Rape**: using abuse or aggressive behavior to coerce others into having sexual relations with them against their will.
- **Vandalism**: the act of causing intentional harm or destruction to public or private property, or damaging public property.
- **Trafficking**: the act of dealing or trading in illegal substances.
- **Assault**: the act of physical attack.
- **Murder/Homicides**: the act of taking someone's life through violence.

Table 4 presents the frequency of crime types studied in the collected research papers. As shown in the table, robbery is the most studied crime type, followed by murder/homicides and burglary with 51, 41, and 39 papers each, respectively. Most of the research papers studied more than one crime type. For instance, the research paper A100, (Kouziokas, 2017b), covered the following crime types: homicide, kidnapping, narcotics, theft, robbery, sexual assault, assault, and use of weapons.

5.2. Crime prediction techniques

In this section, we present the findings of RQ2, which concerns the type of techniques used in crime prediction and the ML approach.

There are two basic approaches to AI and ML supervised and unsupervised learning. The key difference is that supervised learning utilizes labeled data to predict the results easily, whereas unsupervised learning does not. However, between the two approaches, there are other differences, gaps, and key areas in which one approach exceeds the other.

Supervised learning is a method characterized by the use of labeled datasets. The datasets are intended to train or track algorithms to accurately identify data or predict results. The model will calculate its own precision and learn over time by using labeled inputs and outputs. Moreover, supervised learning can be categorized into two forms of datamining problems: classification and regression.

- Classification ML utilizes an algorithm to classify and categorize test data, such as differentiating dogs from cats. Another example from the real world is identifying spam emails and categorizing them into a separate folder in your mail. Support vector machines, decision trees, random forests, and linear classifiers are examples of classification ML algorithms.
- Regression ML is another form of supervised learning that utilizes an algorithm to establish a relationship among dependent and independent variables. Furthermore, regression models are constructed for predicting numerical values. Logistic regression, polynomial regression, and linear regression are examples of regression ML algorithms.

Unsupervised learning is a method that analyzes and clusters

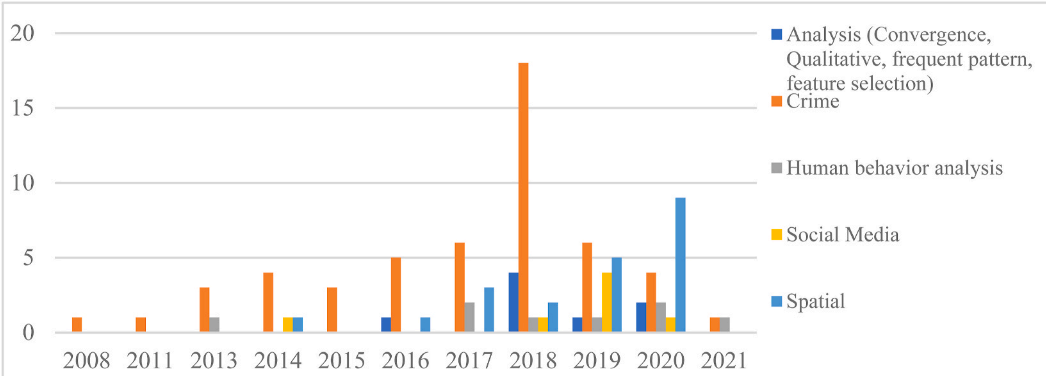

Fig. 2. Crime type analysis distribution over time.

Table 4
Frequency of the categories of crimes studied by researchers.

Category of Crime	Freq.	Category of Crime	Freq.	Category of Crime	Freq.
Robbery	51	Fraud	5	Carnapping	2
Murder/Homicides	41	Arson	5	Trafficking	3
Burglary	39	Cybercrime/Hacking	4	Disorder	3
Theft	35	Disorder	3	Attack	1
Assault	35	Vandalism	3	Mascare	1
Vehicle Larceny	18	Injury	3	Children offense	1
Rape	17	Stalking	3	Graffiti crimes	1
Drugs/Narcotics	15	Gambling	2	Dowry death	1
Violence	11	Homeless crimes	2	Cattle rusting	1
Kidnapping	11	Foreclosed	2	Physical injury	1
Sexual assault	11	Dacoits	2	Fighting	1
Gun/weapons/Shooting	7	Accidents	2	Attack	1

unlabeled datasets. This process can find a hidden pattern in data without the need for human interference. In addition, this method can be divided into three major types: clustering, association, and dimensionality reduction.

- Clustering is an unlabeled data grouping strategy based on similarities or differences. For instance, the K-means algorithm allocates similar data points into clusters (groups), with the K value being the group size.
- Association is another unsupervised form of ML that uses various rules to obtain links between variables within a dataset.
- Dimensionality reduction is a training strategy used when a given dataset has a high number of features (or dimensions). The data input is reduced to a manageable size, and data integrity is also preserved.

The difference between supervised and unsupervised learning is whether the algorithm utilizes labeled input and output data. In supervised learning, iterative predictions of the data and adjustments for the correct response are given to the algorithm from the training data. Unsupervised learning attempts to detect the structure of unlabeled data in the algorithm. However, an approach that works between the two is known as semisupervised learning, which is used when the training data include both labeled and unlabeled data. The semisupervised approach is preferable when the dataset includes a small number of labeled samples compared to unlabeled samples. This is considered to be a challenging approach; however, it is still being deployed by researchers. For example, a semisupervised approach was conducted in A108 (Tundis et al., 2019), exploiting bags of words in evaluating textual information such as tweets related to crimes.

According to Fig. 3, the most utilized approach in crime prediction is supervised learning, which comprises 31% of papers. Moreover, as some papers utilized more than one ML algorithm, 22% of the research papers collected used both a supervised and unsupervised approach. However, only 10% applied unsupervised learning. Surprisingly, only 1% used the semisupervised approach, which shows that this approach is not often applied in the field of crime prediction. Finally, 36% of the papers did not specify which approach they followed.

Several techniques have been applied by research papers for crime prediction. We found 64 different techniques in the selected research papers. Moreover, most of the techniques are ML algorithms. Table 12 in the Appendix presents the techniques applied by researchers. According to the table, the most applied algorithm utilized in crime prediction is random forest and naïve Bayes. Twenty-five papers applied random forest and 20 papers applied naïve Bayes, whereas 17 papers utilized a decision tree algorithm. Additionally, most of the selected papers built hybrid models that consist of several ML algorithms. For example, A8 used an artificial neural network (ANN) and an artificial bee colony (ABC) algorithm (Anuar et al., 2015). Another example is A16, where logistic regression was applied with a neural network (Rummens et al., 2017). On the other hand, some papers used a standalone model; for instance, A14 used a decision tree (Chatterjee et al., 2019), A22 used naïve Bayes (Vural & Gok, 2017), and A32 used a hidden Markov model (Srivastava et al., 2008).

5.3. Evaluation and performance metrics for ML algorithms

In this section, we present the finding of RQ3, which discusses the estimation accuracy of the models used by focusing on four aspects: accuracy metric, accuracy value, the dataset for construction, and model validation methods.

We list the most widely used evaluation and performance metrics in crime prediction. We found 43 different performance metrics utilized in the selected research papers. A total of 19 research papers did not specify or discuss evaluation metrics. Table 5 presents the performance metrics discussed and applied in the collected papers. We categorized the performance metrics shown in the table into broader groups. For instance, the mean error category includes the mean absolute percentage error, mean absolute error, mean squared error, root mean squared error, mean relative error, and error rate. Furthermore, some metrics have several notations and names, such as the true positive rate, which is *also* known by sensitivity, detection rate, and recall. Another example is the false-positive rate, which is also known as the false alarm rate.

According to Table 5 and Fig. 4, the most applied performance metric is the mean error, which is used by 59 papers, followed by accuracy and the true positive rate used by 45 and 38 papers, respectively. Most of the collected research papers used several performance metrics, as shown in Table 13 in the Appendix. For instance, the true positive rate, false-

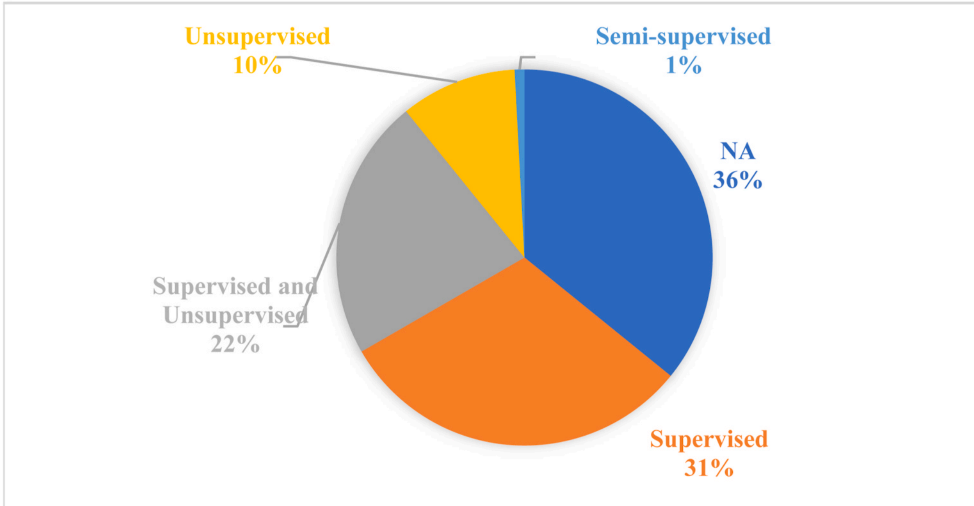

Fig. 3. Machine learning algorithms type.

Table 5
Performance metric categories.

Performance Metric -Main Category	Performance Metric - Specific types	Freq.	%
Mean Error	Mean Absolute Percentage Error (MAPE) Mean Absolute Error (MAE) Mean Squared Error (MSE) Root Mean Squared Error (RMSE) Mean Relative Error (MRE) Error rate	59	21%
Accuracy	Directional accuracy (DA) Predictive Accuracy Index (PAI) Classification accuracy	45	16%
True Positive Rate (TPR)	Sensitivity Detection Rate Recall unweighted average recall (UAR) Hit rate Correct Finds Correctly Classified	38	14%
F-measure	Macro-F1 Micro-F1	26	9%
Precision	Positive Prediction Value	26	9%
Area Under Curve (AUC)	Receiver Operating Characteristic (ROC) Area Under Receiver Operating Characteristic (AUROC)	20	7%
Correlation coefficient	Pearson Correlation Coefficient (PCC) coefficient of determination (R^2) Rank Correlation Correlation Matrix	9	3%
False Positive Rate (FPR)	False Alarm Rate (FAR) Correct exclusion	9	3%
Time	Elapsed Time Detection Time Delay	7	3%
Confusion matrix	na	5	1%
True Negative Rate (TNR)	Specificity false hits	4	1%
False Negative Rate (FNR)	Misclassified Incorrect exclusions	4	1%
prediction index	Predictive Efficiency Index (PEI) Recapture Rate Index (RRI) Adjusted Rand Index (ARI)	4	1%
PAI (Personal Activity Intelligence)	na	3	1%
Kappa Statistic	na	2	0%
Memory usage	na	1	0%
p-value	na	1	0%
Jensen-Shannon Divergence (JS)	na	1	7%
No applied Performance metric	na	19	21%

positive rate, recall, F-measure, precision, Kappa statistic, time to build the model, mean absolute error, relative absolute error, root relative squared error, and prediction accuracy were used in A106. On the other hand, there are many papers that used only accuracy as a performance metric, such as A12, A13, A17, A28, A39, A41, and A48. Using a single performance metric is not an effective or efficient detection method. Accuracy measures can sometimes lead to partial results in the performance indicator, as in a skewed dataset. Table 13 in the Appendix presents the ID of the paper along with the performance metric, value, validation methods, and the dataset used for the collected research papers.

We identified 40 different datasets employed in crime prediction models. Table 8 in the Appendix shows the type of dataset collected, details about it, availability, duration, and frequency of use. As researchers aim to predict crimes, most of the utilized datasets are records of violent crimes, police data portals, and national crime records of specific countries. As shown in Table 8, 22 different regions' crime records are collected. According to Fig. 5, Chicago, India, and the US are the regions with crime datasets that are most used in selected papers with frequencies of 19, 13, and 12, respectively. Furthermore, some papers use tweets, newspapers, compliant data, and images of weapons as datasets for their prediction models.

5.4. The tools, strength, and limitations of prediction techniques

In this section, we present the findings of RQ4, which discuss the tools applied in the selected research papers, the strengths and weaknesses of the prediction models, and the limitations and future directions of crime prediction.

We found 20 different tools that are utilized for crime prediction. As presented in Table 6, the most applied tool is Weka, as it was used by 11 research papers. Moreover, Python and R language programming languages are applied widely. Furthermore, in Python, several libraries and packages are available for the geospatial aspect. For example, GeoPandas, Shapely, and PySAL are frequently used. Moreover, the geographic information system (GIS) framework is one of the main frameworks used in this field, as there are many tools to utilize geographical information, such as ArcGIS, QGIS, and Plenario.

As we discussed before in RQ2, several ML models have different strengths and weaknesses. For example, in A83, where K-NN and random forest are used, their approach is appropriate for nonlinear datasets with high-order complexity. In A82, the authors used the Bayesian hierarchical model, and they argue that their model not only increases the accuracy of mobility-based crime predictors significantly,

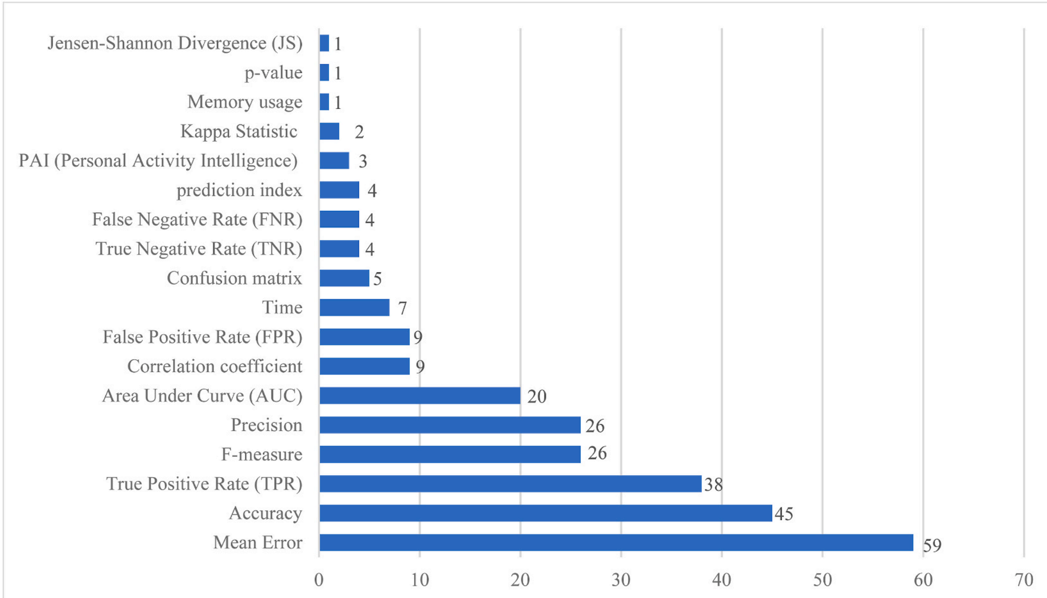

Fig. 4. Histogram of performance metrics.

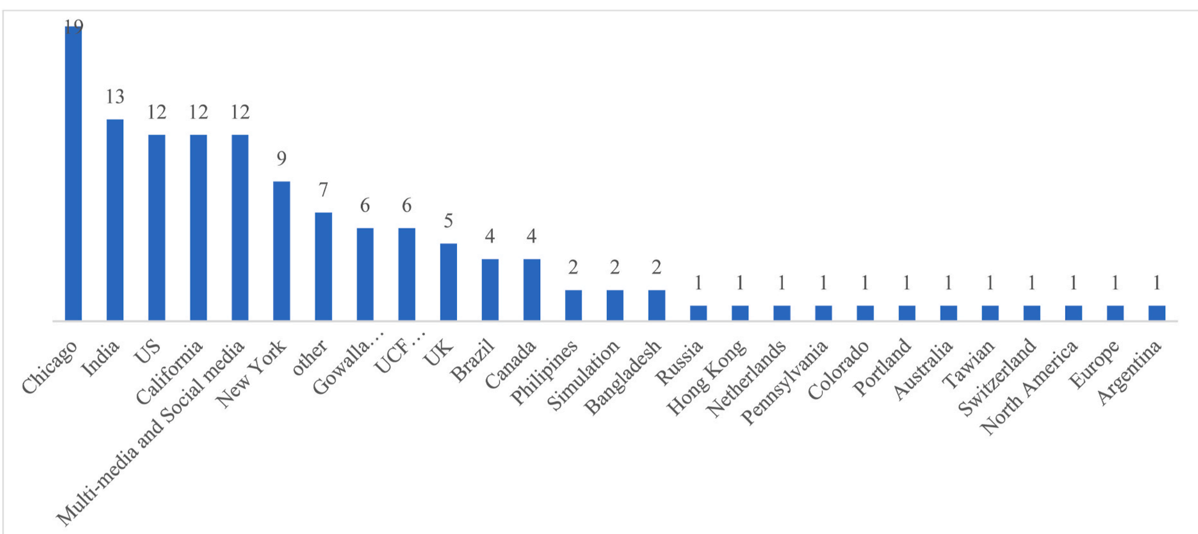

Fig. 5. Frequency of utilized datasets.

but also delivers fair predictions that balance performance among protected categories. By contrast, A87 proposed a model that utilizes the extremely randomized trees (Extra-Trees) model and the Least Absolute Shrinkage and Selection Operator (LASSO) method for their model. However, the weakness of their proposed approach is due to the nonlinear structure of social data, making prediction accuracy relatively low. Table 9 in the Appendix presents some of the strengths and weaknesses of the selected research papers.

As presented in Table 9, we can conclude that applying the random forest model in crime prediction is very useful, which is due to its ability to handle colinear features, high dimensionality, and heterogeneous space, which effectively avoids the overfitting problem and according to A93, gives accurate long-term crime forecasting (Rumi et al., 2018; Umair et al., 2020; Wheeler & Steenbeek, 2020). On the other hand, there are several limitations to the random forest model. For example, time constraints limit usability since learning the model and building the tree are iterative processes. Furthermore, data availability and limited resources also limit this model. Deep learning techniques have shown promising results in the field of crime prediction. Techniques such as deep neural networks, partially generative neural networks, hierarchical recurrent neural networks, enhanced associative neural networks, etc., show several strengths and advantages due to their robustness. For example, they have higher AUROCs, capture the significance of crime occurrences across time periods, predict crime occurrences in many categories in each sector of a city, allow for the replication, transmission, and continual enhancement of the knowledge model, and provide a more objective basis for comparison (C. Huang et al., 2018; Lin et al., 2018; Seo et al., 2018).

Another aspect to look at is the limitation and future direction of crime prediction. For example, in A91, the research paper's future

Table 6
Tools that are used in the Selected Research Papers.

Tool/Language	Details, Packages, types	Freq.	%
WEKA	Datamining	11	**23%**
Python	Shapely, PySAL, GeoPandas, Folium, scikit-learn, Orange, emcee, Matplotlib, LabelEncoder, OneHotEncoder	8	**17%**
R Studio	R-programming, R statistical software, Glmer from Lme4 package	8	**17%**
GIS	Plenar.io platform, ArcGIS, QGIS, Mobile GIS	8	**17%**
Graphviz	Graph visualization	1	**2%**
Prophet	Python & R-language	1	**2%**
MALLET	Machine learning	1	**2%**
NetBeans	Java	1	**2%**
Anaconda	Python & R-language	1	**2%**
Plenario platform	Spatio-temporal open data	1	**2%**
Tensorflow	Machine learning library	1	**2%**
Z-Crime tool	Datamining	1	**2%**
PyTorch	Machine learning library	1	**2%**
GMAPI	Na	1	**2%**
CARDWATCH	Na	1	**2%**
MATLAB	Na	1	**2%**
GRETL	Na	1	**2%**

direction is to add more location information to the crime tweets, as these will be useful in detecting the location of crimes. According to A87, they claim that their limitation is due to the lack of data availability. Table 10 in the Appendix presents some of the future directions and limitations of the scientific papers collected. A future aim in this research, as shown in Table 10, is to apply the learning of crimes to a larger variety of urban data forecasting applications. Unsupervised learning is used, for instance, as is novelty detection and outlier detection for highly imbalanced classifications. From a data standpoint, we look for more data sources that help in the crime prediction sector, such as social media.

The selected papers were used to derive the strengths and limitations of ML approaches. As a result, some of them could just represent the researchers' viewpoints and be untrustworthy. We give only the synthesis of strengths and limitations that are explicitly indicated in the selected research to maximize the trustworthiness of the synthesized results. Furthermore, the research quality evaluation procedure helps verify that these strengths and shortcomings come from studies of acceptable quality. Nonetheless, caution must be exercised when dealing with any implications formed from these synthesized results.

6. Limitation of this review

In this systematic literature review, the limitation is restricted to journals and conferences in relation to AI in crime prediction. We omitted a large number of irrelevant articles by using our search approach in the early stages of the research. This ensured that the research papers chosen met the criteria for this study. We assume, however, that this analysis has been further strengthened by the use of additional sources. In addition, for the quality evaluation, the same approach applied because we used a firm QAR.

7. Conclusion and future work

This systematic literature review explored crime prediction that has been approached with AI techniques. It examined scientific papers from several perspectives: the research in crime prediction with respect to the type and category of the crime, time of the study, and the kind of crime most researchers have been discussing. Then, we reviewed the techniques used and their approaches. In addition, we examined several factors, consisting of the type and category of the crimes considered. The main ML algorithms that are used to predict crimes in relation to how accurate they are and determining what makes a certain training model suitable with the data provided. In addition to the strengths and limitations of the algorithm. Our conclusion highlights are as follows:

- RQ1: The results of this research question show that crimes and spatial are the two most applied categories in analyzing crimes. Furthermore, RQ1 illustrates the crime analysis type distribution over time. We found that most of the research papers used crime density as an approach for analyzing prediction. However, in 2020, analyzing spatial data was the aspect that was the most frequently performed. Additionally, we found that robbery, murder, and burglary are the most common crime types studied by researchers, with frequencies of 51, 41, and 39, respectively.
- RQ2: The most applied algorithm utilized in crime prediction is random forest and naïve Bayes. Twenty-five papers applied random forest and 20 papers applied naïve Bayes, whereas 17 papers utilized the decision tree algorithm. In addition, most of the scientific papers used hybrid models that applied more than one ML algorithm. Furthermore, the most utilized approach in the field of crime prediction is the supervised learning approach, with a percentage of 31%. Moreover, 22% of the research papers collected used a supervised and unsupervised approach. 10% applied unsupervised learning.
- RQ3: The most applied performance metric is the mean error, which was used by 59 papers, followed by accuracy and the true positive rate, which were used by 45 and 38 papers, respectively. Most of the collected research papers used several performance metrics. Moreover, we identified 40 different datasets employed in crime prediction models. Twenty-two different regions' crime records were collected. Chicago, India, and the US were the regions with crime datasets that were most used in the selected papers with frequencies of 19, 13, and 12, respectively.
- RQ4: The most applied tool is Weka, as it was used by 11 research papers. Moreover, Python and R language programming languages were applied widely. In addition, RQ4 presents some of the advantages and disadvantages of the proposed ML algorithms in the selected scientific articles. Finally, RQ4 discusses some of the limitations and future directions of crime prediction. For instance, one of the future directions is adding more location information to the crime tweet to benefit and improve the detection of crime location.

According to the findings of this study, existing AI-technologies can perform reasonably well in crime prediction and prevention. AI technologies have been shown to give valuable information in crime prediction with a high level of precision. AI technology improved efficiency especially in the usage of application in spatiotemporal crime hot spot identification. Moreover, the use of hybrid models in crime prediction produced successful performance. This is encouraging other researchers to perform more study on hybrid model development.

We want to use the knowledge gained from this review to deploy and develop hybrid models in crime prediction as part of our future work. Moreover, we propose to undertake experiments to test and enhance the weaknesses and limitations discussed in this review and improve the performance of our solution. In addition, one of the key focuses on our future direction is to examine the technical aspects in the depth of crime prediction.

Authors' contribution

Fatima Dakalbab: Methodology, Writing, Visualization, Software, Literature Review.
Manar Abu Talib: Conceptualization, Funding acquisition, Writing-Original draft preparation, Supervision (Corresponding Author).
Omnia Abu Waraga: Data curation, Resources, Literature review.
Ali Bou Nassif: Conceptualization, Methodology, Software, Investigation, Validation, Writing- Reviewing and Editing.
Sohail Abbas: Data curation, Software.
Qassim Nassir: Conceptualization, Funding acquisition, Writing-Reviewing and Editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table 7
QAR Score

QAR Score	Frequency	Paper ID
5	7	A19, A20, A37, A51, A90, A97, A118
5.25	4	A1, A18, A31, A83
5.5	1	A26
5.75	4	A33, A82, A108, A115
6	4	A12, A21, A48, A100
6.25	8	A15, A27, A35, A38, A46, A52, A93, A94
6.5	6	A25, A36, A45, A67, A68, A109
6.75	2	A34, A85
7	3	A7, A10, A60
7.25	9	A39, A40, A41, A42, A47, A49, A56, A59, A77
7.5	8	A3, A32, A50, A55, A95, A110, A113, A117
7.75	10	A2, A14, A24, A28, A29, A53, A54, A71, A92, A99
8	11	A5, A17, A43, A44, A78, A88, A96, A104, A114, A116, A119
8.25	5	A69, A81, A86, A87, A101
8.5	3	A66, A76, A107
8.75	14	A8, A16, A57, A58, A63, A64, A65, A80, A89, A91, A102, A103, A105, A111
9	8	A6, A9, A13, A72, A79, A84, A112, A120
9.25	5	A22, A30, A73, A74, A106
9.5	3	A61, A62, A98
9.75	4	A4, A11, A70, A75
10	1	A23
Grand Total	**120**	

Table 8
Utilized Datasets per Category

Country/State	City	Details	Open	From	To	%	Freq.
Chicago Illinois	* Na	*Police Data Portal *Violent crimes * Police Data Portal * Citizen Law Enforcement Analysis and Reporting (CLEAR)	yes	* 2001 * 2007 * Jan 1st, 2017 *2013	* 2019 * 2012 * Dec 31st, 2017 *2017	15%	19
India	* Gujarat * Bureau * Bengaluru	* Police department * National Crime records * GVK Emergency Management and Research Institute	Yes	Na	Na	10%	13
US	* Cambridge - England * Cheltenham - England * Northeast * Southern *Baltimore	* Crime Analysis Unit Police Department * Crime data * police department - residential burglary report *Department of public safety at USC *Baltimore Police Department's Victim Based Crime Data	Na	*Na *Na *Jan 1st, 2006 * Feb 10, 2010	*Na *Na *Dec 31st, 2009 * Aug 4, 2016	9%	12
California	* San Francisco * Mississippi * Los Angeles	*Homicide dataset *Na *Police department	Na	*1981 *Na *2014	*2014 *Na *2016	9%	12

(continued on next page)

Table 8 (*continued*)

Country/State	City	Details	Open	From	To	%	Freq.
Multi-media and Social media	Na	* News sites, blogs, RSS feeds * Images of Knives, guns, and blood * Surveillance videos * Titter * Open street map	Na	Na	Na	9%	12
New York		* Police department * Crime data * Crime data	Yes	*2015 *July 1, 2012 *Jan 1, 2014 * 2014	*2017 *June 30, 2013 *Dec 31, 2014 *2015	7%	9
Other	Na	* Point of Interest * Public Service Complaint Data * Taxi flow data * News data * Global Terrorism Database (GTD)	Na	*Na *Na *Na *2011 *2015	*Na *Na *Na *2019 *2016	6%	7
Gowalla Foursquare	Na	Na	Na	*Feb 2009	* Oct 2010	5%	6
UCF UCI	Na	*Crime dataset * The Communities and Crime Unnormalized Data Set	yes	Na	Na	5%	6
UK	* London Borough	*Profiles (68 metrics) * police crime data	Na	Na	Na	4%	5
Brazil	*Na *Fortaleza *Cearra	* healthcare system	Yes	*Na * July 2016 * July 2016	Na * Nov 2017 * Nov 2017	3%	4
Canada	* Edmonton * Vancouver	* Last 15 years	Yes	Na	Na	3%	4
Philippines	*Misamis Occidental *Manila	*Na *Manila Police District (MPD)	Na	*Na *2012	*Na *2016	2%	2
Bangladesh	Na	*Dhaka Metropolitan Police (DMP)	Na	*June 2013	* May 2014	2%	2
Russia	* Saint-Petersburg	* Crime records	Private	1/1/2014	2/28/2017	1%	1
Hong Kong	* Guangzhou	* traffic violation	Na	2012	2016	1%	1
Netherlands	* Amsterdam	* Police Department	Na	Na	Na	1%	1
Pennsylvania	* Philadelphia	Na	Na	Na	Na	1%	1
Colorado	* Denver	Na	Yes	Na	Na	1%	1
Portland	* Oregon	* Crime occurrences	yes	* March 2012	* December 2016	1%	1
Australia	* Queensland	Na	Na	Na	Na	1%	1
Taiwan	* Taoyuan	* Vehicle theft	Na	* Jan 2015	* April 2018	1%	1
Switzerland	* Aargau	*burglary incidents	Na	* Jan 14, 2014	* Jan 13, 2017	1%	1
Mexico	Na	* Secretary-General of National Public Security * The National Council for the Evaluation of Social Development Policy	Na	* 2011	* na	1%	1
Belgium	Na	* local police department	Na	* 2007	* 2017	1%	1
Argentina	* Buenos Aires	Na	Na	*2016	*2019	1%	1

Table 9
Strength and Weakness of ML Models

ID	Strength, weakness	Model
A54	* Positive prediction is guaranteed by count-based regression models.	Negative binomial regression
A55	*Able to detect high potential hotspots at which crime will have the highest chances of being committed in the future by setting a larger α	ensemble spatiotemporal pattern (ESTP)
A56	*More robust to different time granularities	temporal-spatial correlations
A59	*Does not overfit the training data, resulting in near-optimal predicting on previously encountered events.	Genetic programming – LSGP
A60	*More robust and has higher AUROCs	Partially Generative Neural Networks (PGNN)
A62	*The feature space is heterogeneous and high-dimensional. *It can handle with colinear features and will not make any assumptions about data on firsthand.	Random Forest
A63	*Captures the significance of crime occurrences across time periods. * Predicts crime occurrences in many categories in each sector of a city.	Category Dependency Encoder + hierarchical Recurrent neural network + Multilayer Perceptron (MLP)
A66	* Allows for the replication, transmission, and continual enhancement of the knowledge model, as well as a more objective basis for comparison.	Deep Neural Networks
A67	* Accurate geographical and functional affinity, activity preferences, and daily schedules descriptions for places and users *Applications in a variety of situations are possible.	feed-forward neural networks + Spatio-Temporal Embedding Similarity
A73	* Can be used to designate priority regions targeted by other nonpolice agencies	Risk Terrain Modeling
A74	* Neural network-based methods might capture multidimensional spatial-temporal data's complex underlying structures in a nonlinear manner.	"Multi-View and Multi-Modal Spatial-Temporal learning (a multimodal pattern fusion module + a hierarchical recurrent framework)"
A75	* Effectively predict crime activity-related features.	"Fireflies-based fuzzy cognitive map neural networks (FFCM), Enhanced associative neural networks (EANN)"
A82	* Not only will this improve the accuracy of mobility-based crime predictors, but it also ensures that performance is balanced across protected groups.	* Bayesian hierarchical model

(continued on next page)

Table 9 (*continued*)

ID	Strength, weakness	Model
A83	* This algorithm works well with datasets that are nonlinear and have a high order of complexity.	* K-NN * Random forest
A84	(−) Learning the model is a time-consuming iterative process, rendering it unsuitable for use as an online tool. (−) This method is ineffective for streets with little or no data.	* k-NN predictions * demographic features *Weighted Multimodal Latent Dirichlet Allocation (WMLDA)
A86	* Relatively resistant to overfitting, which is useful in this case because there are only a few thousand grid cells to learn from and almost a hundred POI properties (SVM, Random Forest) * Capable of using the fullest of available attributes without overfitting - (SVM, Random Forest)	"logistic regression, support vector machines, decision trees, and random forests"
A87	(−)Because of the nonlinear nature of social data, LASSO prediction accuracy is relatively low.	* Extremely randomized Trees (Extra-Trees) "Least Absolute Shrinkage and Selection Operator (LASSO)"
A88	* No iteration steps are required for maximizing or decreasing likelihood or cost functions, as in the EM method and other machine learning techniques. * The DDGF technique allows us to discover the buried causal effects of criminal events.	"self-exciting point process models (SEPP)" * data-driven Green's function * prospective hotspot maps * Expectation Maximization
A93	* Accurate long-term crime forecasting in micro places with respect to other common techniques	Random Forests
A106	* Simple to comprehend and implement in cybercrime investigations	J48 Decision Tree
A110	* Less sensitive to spatiotemporal resolution, which allows it to perform effectively in sparse areas.	Random Forest Regression (RFR) Support Vector Regression (SVR) Multi-Layer Perceptron Regression (MLPR)
A113	* Effectively avoid the problem of overfitting	Random forest
A118	* Secure, user-friendly and accurate with predicting criminal activity	K-Means Clustering

Table 10
Limitation and Future work of Selected Research Papers

ID	Limitation/Future work	ML type
A63	(F) extend our method to a broader range of urban data forecasting applications. (F) investigate additional data sources (e.g., social media data) in addition to the commonly used data.	Category Dependency Encoder + hierarchical Recurrent neural network + Multilayer Perceptron (MLP)
A65	(F) examine whether similar results exist outside of the United States by utilizing various sources of social media activity.	random forest (RF) + gradient boosting machines (GBMs) + feed-forward artificial neural networks (ANNs) + Rolling window prediction
A70	(F) enhancing our solution by using more road network characteristics as network edges.	Kernel Density Estimation (KDE) + Hierarchical clustering (HC)
A71	(F) Sorting tweets based on the sort of hatred expressed	LTSM + MLP neural network
A72	(F) use additional grouping models to improve crime prediction accuracy and overall performance.	naïve Bayes + SVM + LASSO feature selection analysis
A74	(F) expanding the current strategy to discover the causes of distinct categories aberrant events.	Multi-View and Multi-Modal Spatial-Temporal learning (a multimodal pattern fusion module + a hierarchical recurrent framework)
A77	(F) investigate additional unsupervised learning strategies for highly imbalanced categories.	hyperensemble
A79	(F) investigating more micro scoping predictive modeling by including more community and social media data	Long Short-Term Memory (LSTM)
A83	(L) time constraints, data availability, and a limited resources	K-NN + Random forest
A84	(L) since learning the model is an iterative process that takes time, it is inappropriate for use as an online technique. (L) This method cannot be applied to streets with little or no data. (F) examine the influence of discovered street kinds in other applications such as pedestrian flow prediction and land price estimation.	kNN predictions + demographic features latent street types discovered by Weighted Multimodal y Latent Dirichlet Allocation (WMLDA)
A86	(F) test the efficacy of POI features for crime prediction in a variety of cities. (F) investigate the effect of grid resolution on prediction quality, as well as the efficacy of more refined spatial aggregation and hotspot detection methods, such as variable-resolution grids and kernel density estimation.	logistic regression, support vector machines, decision trees, and random forest
A87	(L) a large amount of data is unavailable. (L) The LASSO model's prediction accuracy is generally low due to the nonlinear nature of social data.	Extremely randomized Trees (Extra-Trees), Least Absolute Shrinkage and Selection Operator (LASSO)
A89	(F) improve CSAN performance by including some interpretable variables and linking them to real-world statistical indices to make the model more explainable and comprehensive.	"variational autoencoders, context-based sequence generative neural network
A90	(F) extend this work by establishing an optimization model, applying it to large amounts of data, and generating findings based on a comparative comparison of several ML algorithms and others such as Genetic Algorithms and deep learning algorithms.	Scaled algorithm
A91	(F) employ additional classifiers to evaluate the efficacy of the suggested method. (F) include location information in the crime tweet to assist police in locating the crime scene.	Random Forest
A92	(F)experiment with our model on different cities and nations with sparse spatiotemporal data to demonstrate its potential application in broader sectors. (F)incorporate external factors	gated localized diffusion network (GLDNet)

Table 11
Selected Research Articles

Ref	ID	Title
Letourneau et al. (2018)	A1	"The Effects of Neighborhood Characteristics on Crime Incidence"
Kim et al. (2019a)	A2	"Crime Analysis Through Machine Learning"
Singh et al. (2018)	A3	"Data Mining for Prevention of Crimes"
Mittal et al. (2019)	A4	"Monitoring the Impact of Economic Crisis on Crime in India Using Machine Learning"
Alves et al. (2018)	A5	"Crime Prediction Through Urban Metrics and Statistical Learning"
Ingilevich and Ivanov (2018)	A6	"Crime Rate Prediction in the Urban Environment Using Social Factors"
Orong et al. (2018)	A7	"Mitigating vulnerabilities through forecasting and crime trend analysis"
Anuar et al. (2015)	A8	" Hybrid Artificial Neural Network with Artificial Bee Colony Algorithm for Crime Classification "
Bogomolov et al. (2014)	A9	"Once Upon a Crime: Towards Crime Prediction from Demographics and Mobile Data"
Tayal et al. (2015)	A10	"Crime detection and criminal identification in India using data mining techniques"
Das and Das (2019)	A11	"Application of Classification Techniques for Prediction and Analysis of Crime in India"
Alkhaibari and Chung (2017)	A12	"Cluster Analysis for Reducing City Crime Rates"
Jin and Deng (2017)	A13	"A Comparative Study on Traffic Violation Level Prediction Using Different Models"
Chatterjee et al. (2019)	A14	"An Approach Towards Development of a Predictive Model for Female Kidnapping in India Using R Programming"
Borowik et al. (2019)	A15	"Time Series Analysis for Crime Forecasting"
Rummens et al. (2017)	A16	"The Use of Predictive Analysis in Spatiotemporal Crime Forecasting Building and Testing A Model In urban Context"
Abdul Jalil et al. (2017)	A17	"A Comparative Study to Evaluate Filtering Methods for Crime Data Feature Selection"
(S. Kumar & Toshniwal, 2016)	A18	"A Novel Framework to Analyze Road Accident Time Series Data"
Chackravarthy et al. (2018)	A19	"Intelligent Crime Anomaly Detection in Smart Cities Using Deep Learning"
Kouziokas (2017a)	A20	"The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban environment"
Nasridinov et al. (2016)	A21	"Application of Data mining for Crime Analysis"
Vural and Gok (2017)	A22	"Criminal prediction using Naive Bayes theory"
Sakhare and Joshi (2014)	A23	"Criminal Identification System Based on Data Mining"
Ku and Leroy (2014)	A24	"A decision support system: Automated crime report analysis and classification for e-government"
Gerber (2014)	A25	"Predicting crime using Twitter and kernel density estimation"
(T. Wang et al., 2013)	A26	"Learning to Detect Patterns of Crime"
Feng et al. (2018)	A27	"Big Data Analytics and Mining for Crime Data Analysis, Visualization and Prediction"
(R. Kumar & Nagpal, 2019)	A28	"Analysis and prediction of crime patterns using big data"
Cavadas et al. (2015)	A29	"Crime Prediction Using Regression and Resources Optimization"
Yu et al. (2011)	A30	"Crime Forecasting Using Data Mining Techniques "
Nasridinov et al. (2013)	A31	"A Decision Tree-Based Classification Model for Crime Prediction"
Srivastava et al. (2008)	A32	"Credit Card Fraud Detection Using Hidden Markov Model"
Toppireddy et al. (2018)	A33	"Crime Prediction & Monitoring Framework Based on Spatial Analysis"
Marchant et al. (2018)	A34	"Applying machine learning to criminology: semi-parametric spatial-demographic Bayesian regression"
Al Boni and Gerber (2017)	A35	"Area-Specific Crime Prediction Models"
Wawrzyniak et al. (2019)	A36	"Data-driven models in machine learning for crime prediction"
Sathyadevan et al. (2014)	A37	"Crime Analysis and Prediction Using Data Mining"
Yadav et al. (2017)	A38	"Crime Pattern Detection, Analysis & Prediction"
Kiran and Kaishveen (2019)	A39	"Prediction Analysis of Crime in India Using a Hybrid Clustering Approach"
Catlett et al. (2018)	A40	"A Data-driven Approach for Spatio-Temporal Crime Predictions in Smart Cities"
Babakura et al. (2015)	A41	"Improved Method of Classification Algorithms for Crime Prediction"
Mary Shermila et al. (2018)	A42	"Crime Data Analysis and Prediction of Perpetrator Identity using Machine Learning Approach"
Almaw and Kadam (2019)	A43	"Crime Data Analysis and Prediction using Ensemble Learning"
Sivaranjani et al. (2017)	A44	"Crime Prediction and Forecasting in Tamilnadu using Clustering Approaches"
Li et al. (2018)	A45	"Spatio-Temporal Pattern Analysis and Prediction for Urban Crime"
Mahmud et al. (2017)	A46	"CRIMECAST: A Crime Prediction and Strategy Direction Service"
(M. Saravanan et al., 2013)	A47	"Enabling Real Time Crime Intelligence Using Mobile GIS and Prediction Methods"
Nakib et al. (2018)	A48	"Crime Scene Prediction by Detecting Threatening Objects Using Convolutional Neural Network "
Lin et al. (2017)	A49	"Using Machine Learning to Assist Crime Prevention"
Azeez and Aravindhar (2015)	A50	"Hybrid Approach to Crime Prediction using Deep learning"
Gunduz et al. (2013)	A51	"Predicting next location of twitter users for surveillance"
Mohler (2014)	A52	"Marked point process hotspot maps for homicide and gun crime prediction in Chicago"
Weihong et al. (2016)	A53	"Spatial−temporal forecast research of property crime under the driven of urban traffic factors"
(H. Wang et al., 2016)	A54	"Crime rate inference with big data"
Yu et al. (2016)	A55	"Hierarchical Spatio-Temporal Pattern Discovery and Predictive Modeling"
Zhao and Tang (2017)	A56	"Modeling temporal-spatial correlations for crime prediction"
Misyrlis et al. (2017)	A57	"Spatio-temporal modeling of criminal activity"
Sun et al. (2017)	A58	"SOS: Real-time and accurate physical assault detection using smartphone"
Castelli et al. (2017)	A59	"Predicting per capita violent crimes in urban areas: an artificial intelligence approach"
Seo et al. (2018)	A60	"Partially Generative Neural Networks for Gang Crime Classification with Partial Information"
Kadar et al. (2018)	A61	"Mining large-scale human mobility data for long-term crime prediction"
Rumi et al. (2018)	A62	"Theft prediction with individual risk factor of visitors"
(C. Huang et al., 2018)	A63	"DeepCrime: Attentive hierarchical recurrent networks for crime prediction"
Bowen et al. (2018)	A64	"Ability of crime, demographic and business data to forecast areas of increased violence"
Vomfell et al. (2018)	A65	"Improving crime count forecasts using Twitter and taxi data"
Lin et al. (2018)	A66	"Grid-based crime prediction using geographical features"
Yang and Eickhoff (2018)	A67	"Unsupervised learning of parsimonious general-purpose embeddings for user and location modeling"
Belesiotis et al. (2018)	A68	"Analyzing and predicting spatial crime distribution using crowdsourced and open data"
Xiong et al. (2019)	A69	"On predicting crime with heterogeneous spatial patterns: Methods and evaluation"
Junior et al. (2019)	A70	"A novel approach to approximate crime hotspots to the road network"
Pereira-Kohatsu et al. (2019)	A71	"Detecting and monitoring hate speech in twitter"
Nitta et al. (2019)	A72	"LASSO-based feature selection and naïve Bayes classifier for crime prediction and its type"
Yoo and Wheeler (2019)	A73	"Using risk terrain modeling to predict homeless related crime in Los Angeles, California"

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Table 11 (*continued*)

Ref	ID	Title
(C. Huang et al., 2019)	A74	"MIST: A multiview and multimodal spatial-temporal learning framework for citywide abnormal event forecasting"
Altameem and Amoon (2019)	A75	"Crime activities prediction using hybridization of firefly optimization technique and fuzzy cognitive map neural networks"
Matijosaitiene, McDowald, and Juneja (2019)	A76	"Predicting safe parking spaces: A machine learning approach to geospatial urban and crime data"
Kadar et al. (2019)	A77	"Public decision support for low population density areas: An imbalance-aware hyper-ensemble for spatio-temporal crime prediction"
Matijosaitiene, Zhao, et al. (2019)	A78	"Prediction of hourly effect of land use on crime"
Morshed et al. (2019)	A79	"Viscrimepredict: A System for Crime Trajectory Prediction and Visualization from Heterogeneous data sources"
Zhu et al. (2019)	A80	"An anticrime information support system design: Application of K-means-VMD-BiGRU in the city of Chicago"
Do Rêgo et al. (2020)	A81	"Exploiting points of interest for predictive policing"
Wu et al. (2020)	A82	"Addressing Under-Reporting to Enhance Fairness and Accuracy in Mobility-based Crime Prediction"
Umair et al. (2020)	A83	"Spatiotemporal analysis of web news archives for crime prediction"
Zhang et al. (2020)	A84	"Automatic latent street type discovery from web open data"
Shukla et al. (2020)	A85	"A Multivariate Regression Model for Identifying, Analyzing and Predicting Crimes"
Cichosz (2020)	A86	"Urban crime risk prediction using point of interest data"
(J. Wang, Jin, et al., 2020)	A87	"Crime risk analysis through big data algorithm with urban metrics"
Kajita and Kajita (2020)	A88	"Crime prediction by data-driven Green's function method"
(Q. Wang, Jin, et al., 2020)	A89	"CSAN: A neural network benchmark model for crime forecasting in spatio-temporal scale"
Bandekar and Vijayalakshmi (2020)	A90	"Design and analysis of machine learning algorithms for the reduction of crime rates in India"
Lal et al. (2020)	A91	"Analysis and Classification of Crime Tweets"
Zhang and Cheng (2020)	A92	"Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events"
Wheeler and Steenbeek (2020)	A93	"Mapping the Risk Terrain for Crime Using Machine Learning"
Li et al. (2021)	A94	"Facial expression-based analysis on emotion correlations, hotspots, and potential occurrence of urban crimes"
Rummens and Hardyns (2021)	A95	"The effect of spatiotemporal resolution on predictive policing model performance"
(Y. Y. Huang et al., 2015)	A96	"Mining Location-based Social Networks for Criminal Activity Prediction"
Parvez et al. (2016)	A97	"A Novel Approach to Identify Spatio-Temporal Crime Pattern in Dhaka City"
Baculo et al. (2017)	A98	"Geospatial-Temporal Analysis andClassification of Criminal Data in Manila"
Barreira et al. (2017)	A99	"A Framework for Digital Forensics Analysis based on Semantic Role Labeling"
Kouziokas (2017b)	A100	"The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban"
Bharathi et al. (2018)	A101	"A Supervised Learning Approach For Criminal Identification Using Similarity Measures and KMedoids Clustering"
Yadhunath et al. (2019)	A102	"Identification of Criminal Activity Hotspots using Machine Learning to Aid in Effective Utilization of Police Patrolling in Cities with High Crime Rates"
Rajapakshe et al. (2019)	A103	"Using CNNs RNNs and Machine Learning Algorithms for Real-time Crime Prediction"
(B. Wang et al., 2019)	A104	"Deep Learning for Real-Time Crime Forecasting and Its Ternarization"
Biswas and Basak (2019)	A105	"Forecasting the Trends and Patterns of Crime in Bangladesh using Machine Learning Model"
Palad et al. (2019)	A106	"Document Classification of Filipino Online Scam Incident Text using Data Mining Techniques"
Yuki et al. (2019)	A107	"Predicting Crime Using Time and Location Data"
Tundis et al. (2019)	A108	"Similarity analysis of criminals on social networks: an example on Twitter"
Gao et al. (2019)	A109	"Suspects Prediction towards Terrorist Attacks Based on Machine Learning"
Borges et al. (2019)	A110	"Time-Series Features for Predictive Policing"
Kim et al. (2019b)	A111	"Crime Analysis Through Machine Learning"
Calderon et al. (2020)	A112	"Filipino Online Scam Data Classification using Decision Tree Algorithms"
Yao et al. (2020)	A113	"Prediction of Crime Hotspots based on Spatial Factors of Random Forest"
Qian et al. (2020)	A114	"GeST: A Grid Embedding based Spatio-Temporal Correlation Model for Crime Prediction"
Jha et al. (2020)	A115	"Criminal Behaviour Analysis and Segmentation using K-Means Clustering"
Krishnan & Zhou (2020)	A116	"Predicting Crime Scene Location Details for First Responders"
Tamilarasi and Rani (2020)	A117	"Diagnosis of Crime Rate against Women using kfold Cross Validation through Machine Learning Algorithms"
Sangani et al. (2019)	A118	"Crime Prediction and Analysis"
Aldossari et al. (2020)	A119	"A Comparative Study of Decision Tree and Naive Bayes Machine Learning Model for Crime Category Prediction in Chicago"
Forradellas et al. (2021)	A120	"Applied Machine Learning in Social Sciences: Neural Networks and Crime Prediction"

Table 12
ML Techniques in Selected Research Papers

Category	Method	ID	Freq
Clustering	K- Nearest Neighborhood Clustering	A1, A2, A11, A19, A21, A27, A33, A39, A42, A83, A84, A111, A117	13
	K- Means Clustering	A3, A7, A10, A12, A18, A21, A44, A47, A80, A115, A118	11
	agglomerative clustering	A12, A44	2
	K-Medoids Clustering	A101	1
	Hierarchical clustering (HC)	A70	1
	Multi-clustering	A55	1
Trees	Random Forest	A4, A5, A9, A11, A27, A29, A43, A50, A61, A62, A64, A65, A68, A81, A83, A86, A91, A93, A96, A98, A99, A107, A110, A112, A113	25
	Decision tree, J48	A1, A2, A4, A14, A23, A31, A37, A43, A86, A98, A99, A106, A107, A109, A111, A112, A119	17
	Extra-Tree	A61, A87, A107	3
	Decision stump	A98	1
Association	Association rules	A1, A3, A37	3
Regression	Logistic Regression	A6, A16, A24, A78, A86, A95, A112, A116	8
	Linear Regression	A3, A4, A6, A76, A85, A96, A105, A116	8
	Autoregressive integrated moving average (ARIMA)	A7, A40, A45, A69	4
	Neighbor Ridge Regression	A57, A68	2

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Table 12 (*continued*)

Category	Method	ID	Freq
	Support Vector Regression	A68, A110	2
	Negative Binomial Regression	A54	1
	Multilinear Regression	A42	1
	Nonlinear Regression	A15	1
	Bayesian Regression	A34	1
	"Least Absolute Shrinkage and Selection Operator (LASSO)"	A87	1
Neural Networks	Neural Networks (NN)	A4, A8, A13, A16, A30, A36, A42, A46, A51, A80, A89, A100, A114	13
	Multilayer Perceptron (MLP)	A51, A63, A71, A100, A110, A100, A110, A120	8
	Deep Neural Networks	A19, A66, A94, A104	4
	Hierarchical Recurrent neural network (RNN)	A63, A19, A74, A103	4
	Convolutional Neural Network (CNN)	A48, A94, A103, A114	4
	Neural Networks - Back Propagation (NN-BP)	A41, A53	2
	Neural Networks - feed forward (NN-FF)	A65, A67	2
	Partially Generative Neural Networks (PGNN)	A60	1
Spatial	Ensemble Spatio-Temporal Pattern Analysis and Detection	A20, A26, A40, A55, A77	5
	Kernel hotspot maps	A52, A88	2
	Spatio-Temporal Embedding Similarity	A67, A74	2
	Temporal-spatial correlations	A56, A114	2
	Density Based Spatial with Noise	A44	1
	Rolling window prediction	A65	1
other	Naïve Bayes, Bayesian Network	A11, A13, A21, A22, A23, A24, A27, A28, A30, A33, A37, A39, A41 A43, A49, A50, A72, A82, A98, A119	20
	Gradient Boosting, XGBoost	A6, A27, A61, A65, A81, A102, A107	7
	Support Vector Machine (SVM)	A30, A58, A72, A86, A96	5
	Long Short-Term Memory (LSTM)	A69, A71, A79, A103, A114	5
	Kernel Density Estimation (KDE)	A25, A70	2
	Genetic Algorithm (GA)	A53, A59	2
	Category Dependency Encoder/auto encoder	A63, A89	2
	Artificial Bee Colony (ABC)	A8	1
	Adaboost	A11	1
	Cumulative logistic model	A13	1
	Feature Selection and Correlation	A17	1
	Jrip	A23	1
	Hidden Markov Model (HMM)	A32	1
	Hierarchical Models	A35	1
	Multitask learning models	A35	1
	Apriori Algorithm	A37	1
	Particle Swarm Optimization (PSO)	A47	1
	Expectation–Maximization (EM)	A52	1
	Exponential Kernel Function	A58	1
	LASSO feature selection analysis	A72	1
	Risk Terrain Modeling	A73	1
	Generalized Linear Models	A81	1
	Expectation Maximization	A88	1
	scaled algorithm	A90	1
	gated localized diffusion network (GLDNet)	A92	1
	Probabilistic model	A97	1
	Natural Language Processing (NLP)	A99	1
	Semantic Role Labeling (SRL)	A99	1
	Sequential Minimal Optimization (SMO)	A99	1

Table 13
Performance Metrics Evaluations and Values

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
A1	2018	NA	Not Applicable	NA	data from the City of Edmonton, Canada Open Data Portal
A2	2018	NA	39%–44%	NA	Vancouver, Canada
A3	2018	NA	LR = 85.5%	NA	Gujarat Police Department
A4	2019	Correlation coefficient Coefficient of determination Absolute mean error Accuracy	Differs for each crime: DT:88.3 FR = 90.9 LR = 93.5 NN = 92.2	NA	Online free about India (National Crime Records Bureau)
A5	2018	NA	RF = 97%	cross validation	Urban Brazil DATASUS (Brazils Public healthcare System (SUS), Department of Data Processing (DATASUS))
A6	2018	MAE (Crossvalidation) R2 (Crossvalidation) MAE of prediction for grid	MAE: 34 R2: 0.9 MAE of prediction for grid: 470	cross validation	PRIVATE. By the Ministry of Internal Affairs of the Russian federation. Records of crime in Saint-

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Table 13 (*continued*)

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
					Petersburg that were registered from 1/1/2014 to 2/28/2017
A7	2018	NA	Not Applicable	NA	Province of Misamis Occidental, Philippines
A8	2015	Accuracy Precision Recall F-measure	precision = 86.48%	10-fold cross validation	UCI
A9	2014	Acc F1 AUC	NA	5-fold cross validation	Londong Bourough Profiles Dataset (68 different metrics)
A10	2015	accuracy Error Calculation	accuracy of 93.62 and 93.99%	NA	National Crime Records Bureau, Committee to protect Journalists
A11	2018	AUC classification accuracy Precision Recall F-measure Correctly classified Misclassified	90–95%	cross-validation	Records for kidnapping, murder, rape and dowry death in Indian states
A12	2017	accuracy rate	0.57	Internal Validation	Data records of the Stop Question and Frisk Report Database, City of New York, Police Department, NYPD -2015
A13	2017	accuracy rate	Bayesian = 70%	NA	2015 traffic violation data from Guangzhou 2012–2016
A14	2018	Accuracy Precision Recall F1 AUC	86–93% • Average recall score = 0.73 • Average F1 score = 0.82 • Average AUC score = 0.86	NA	Data from the National Crime Records Bureau
A15	2018	mean absolute percentage error (MAPE)	Differs per crime 60–90%	cross-validation	crowd-sourced open datasets
A16	2017	Direct hit rate Precision Prediction index	Differs for each crime 46.57–67.79%	NA	Data from the Amsterdam Police Department
A17	2017	Accuracy	96.94%	10 fold cross validation	UCI
A18	2016	NA	Not Applicable	NA	Data from the Emergency Management Research Institute (GVK-EMRI)
A19	2018	Mean Squared Error, Error Rate	Not Applicable	NA	Large video data set, source not mentioned
A20	2017	Mean Squared Error (MSE)	Not Applicable	NA	City of Chicago Data Portal
A21	2015	Elapsed Time, memory usage	na	NA	Not Applicable
A22	2017	accuracy rate	0.79	cross validation	Not Applicable
A23	2014	Positive Rate, Negative Rate, Recall, Precision, Confusion matrix, Time taken	NB: 71.7% J48: 71% Jrip: 90.5%	NA	Local police stations in India
A24	2014	accuracy rate classification accuracy	LR: 89% NB:87% classification accuracy of system: 94.82%	NA	Crime Video Clips collected from police training videos, commercial & surveillance videos & TV programs
A25	2014	Differs for each crime but not mentioned, only talks about how using Twitter features with KDE improves % AUC	Differs for each crime but not mentioned, only talks about how using Twitter features with KDE improves % AUC: 0.71	NA	Data Portal of the Chicago Police Department
A26	2013	average precision, Sensitivity analysis, Correct hits, Correct finds, Correct exclusions, Incorrect exclusions, False hits	Not Applicable	NA	Crime Analysis Unit of Cambridge Police Department
A27	2018	MSE (mean square error), accuracy	accuracy: 70%	cross validation	Crime data in San Francisco, Chicago & Philadelphia
A28	2019	accuracy rate	Differs per crime 49%–74%	NA	Cheltenham crime data
A29	2015	NA	Not Applicable	NA	UCI's The Communities and Crime Unnormalized Data Set
A30	2011	Precision Recall F1-score Accuracy	F1-score: 73% Accuracy: 0.8875	NA	Northeast City's police department
A31	2013	NA	Not Applicable	NA	Not Applicable
A32	2008	True Positive False Positive Detection time Accuracy	Not Applicable	NA	None, banks do not share data to researchers. Simulation studies were performed
A33	2018	NA	Not Applicable	NA	U.K. Crime data, https://data.police.uk/data/
A34	2018	root mean squared error (RMSE),	Differs for each crime 66–85%	NA	Unit-Record Criminal Incident Dataset provided by the NSW Bureau of Crime Statis-tics and Research (BOCSAR)

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Table 13 (*continued*)

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
A35	2016	NA	Differs for each crime 68%–88%	NA	Crime records from Chicago, Illinois Data Portal: https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2
A36	2018	(MSE)	Not Applicable	NA	Undisclosed police records
A37	2014	NA	NB: >90%	NA	Data collected from different web sites like news sites, blogs, social media, RSS feeds
A38	2017	NA	Not Applicable	NA	legitimate online portal of India
A39	2018	accuracy	NB: 87% KNN: 77%	NA	Not Applicable
A40	2018	MAE, MAPE	Errors 1st Year: 8.68%–11.90% 2 nd Year:7.60%–9.62% 3rd Year:10.14%–18.66%	NA	Chicago's 'Crimes 2001 - present' dataset
A41	2014	accuracy	NB: 90.2–94.1% BP: 65.9%	NA	UCI
A42	2018	NA	0.9164	NA	San Francisco Homicide dataset (1981–2014)
A43	2018	Accuracy TP rate FP rate Precision Recall F-measure	0.82	NA	https://www.denvergov.org/opendata/
A44	2016	Accuracy Precision Recall F-measure	KMC: 84% AC: 92% DBSN: 95%	NA	National Crime Records Bureau (NCRB) of India.
A45	2018	NA	0.921	NA	dataset provided by the University of California-Irvine repository & actual crime statistical data for the state of Mississippi
A46	2016	NA	Not Applicable	NA	dataset provided by Indian national crime records dataset of Gansu, China
A47	2013	Precision Recall F-measure	0.956	NA	Not Applicable
A48	2018	accuracy	0.902	NA	Images of knives, guns and blood
A49	2017	NA	>90%	NA	Not Applicable
A50	2015	NA	DL: 86% RF: 85% NB: 83.5%	NA	Not Applicable
A51	2013	Error Rate	error rate: 3%	NA	50 Foursquare check-ins for each 129 person, the latitude and longitude of each visited place and month and day information of each check-in are extracted from the Foursquare link
A52	2014	accuracy rate	NA	NA	open-source data set consisting of violent crimes occurring in Chicago, Illinois, in the years 2007–2012
A53	2016	square error	Square error: 0.019	NA	spatial temporal data of property crime that occurred at city A located in South China in the period from 2008 to 2012
A54	2016	accuracy rate, p-value, mean absolute error (MAE), and mean relative error (MRE),	MAE: 273.27 MRE: 0.269	NA	crime data of City of Chicago data portal
A55	2016	accuracy, F1-score	accuracy: 80% F1-score: 0.818	10-fold cross-validate	police department of a Northeastern city in the United States, we obtained 4-years of residential burglary report from January 1st, 2006 to December 31st, 2009
A56	2017	average root-mean-square-error (RMSE)	NA	NA	collect crime data from July 1, 2012 to June 30, 2013 in New York City
A57	2017	Mean Squared Error (MSE) and Predictive Efficiency Index (PEI)	NA	NA	public dataset of crime occurrences in Portland, Oregon reported from March 2012 to December 2016
A58	2017	False Negative Rate (FNR), low false alarm rate (FAR), delay	FNR: 11.75% FAR: 0.067 times per day delay: 6.89 s	cross validation	* 100 surveillance videos involving aggravated assaults, and extract the pattern of actions for an individual under assaulting *simulated aggravated assaults which are performed by our volunteers in controlled settings
A59	2017	mean absolute error (MAE)	MAE: 0.0906	p-values obtained for statistical validation procedure	socio-economic data from the 1990 United States Census, law enforcement records from the 1990 United States LEMAS survey and the FBI
A60	2018	AUROC	AUROC: 0.9180	cross validation	Los Angeles Police Department in 2014, 2015, and 201
A61	2018	mean squared error (MSE)	MSE(Random Forest): 0.07 (Extra-tree): 0.22 (Gradient Boosting): 0.23	cross-validation	census data, Foursquare venues data, subway usage data, and taxi usage data

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Table 13 (*continued*)

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
A62	2018	Confusion matrix, Area Under Curve (AUC) under Receiver Operating Characteristic (ROC)	na	10-fold cross validation	One is from Brisbane, the capital city of Queensland, Australia and the other two are from New York City, USA
A63	2018	F1-score, Marco-F1 and Micro-F1	F1-score: 18.7% Marco-F1:0.6836 Micro-F1: 0.6233	NA	real-world datasets collected from New York City (NYC) * Crime Data 1 from Jan 1, 2014 to Dec 31, 2014 * Point of Interests (POIs) * 311 Public Service Complaint Data
A64	2018	positive predictive value negative predictive value sensitivity specificity	positive predictive value = 52.1% negative predictive value = 97.5% sensitivity = 43.4% specificity = 98.2%	NA	*Demographic data: 20 variables from the American Community Survey *Business data:the yearly counts of seven different business types *Historical crime data:24 months of lagged variables on both violent crimes
A65	2018	Mean Square Error (MSE)	NA	cross-validation	* US Census Bureau. * New York City Crime Data * Foursquare * taxi flow data NYC * twitter
A66	2018	Precision, Recall, Accuracy, F1-score	F1-score: 0.4734 Accuracy: 0.8376 Precision: 0.4107 Recall: 0.5708	NA	Vehicle Theft data for Taoyuan City, from January 2015 to April 2018 and Google Place API
A67	2018	Silhouette Index, Adjusted Rand Index (ARI)	Silhouette Index: 0.557 Adjusted Rand Index (ARI): 61%	NA	Foursquare
A68	2018	prediction accuracy	accuracy: 0.8	10-fold cross validation	UK Police Crime Data (2015) Features: * Demographics (DM): Office for National Statistics * POI: OpenStreetMap, Wikimapia, Foursquare * Transportation and Mobility (TM): Transport for London, OpenStreetMap * Land Use (LU): OpenStreetMap * Images (IMG): Flickr
A69	2019	cross-validation and mean squared error	NA	cross-validation	* crime data from February 10, 2010 to August 4, 2016 obtained from Department of Public Safety at University of Southern California (USC) * Los Angeles crime data2 from January 1, 2014 to December 31, 2016
A70	2019	PAI (Personal Activity Intelligence)	NA	NA	crimes that occurred in Fortaleza, Cearra, Brazil between July 2016 to November 201
A71	2019	area under the curve (AUC), Confusion matrix	AUC: 0.828	10-fold cross-validation	novel public dataset on hate speech in Spanish consisting of 6000 expert-labeled tweets
A72	2019	Accuracy, Precision, Recall, and AUC	Accuracy: 97.47 Precision: 92.89 Recall: 86.83 AUC: 0.9184	NA	a criminal record database was downloaded from Chicago data portal, which included all reported crimes from 2001 to 2019
A73	2019	Area-under-the-curve	AUC: 0.925	NA	The Los Angeles Police Department (LAPD)
A74	2019	Macro-F1 and Micro-F1.	Macro-F1: 0.7278 Micro-F1: 0.6979	na	* NYC Crime Data (NYC–C) from Jan 2015 to Dec 2015 * NYC Urban Anomaly Data (NYC-A) from Jan 2014 to Dec 2014 * Chicago Crime Data (CHI–C) from Chicago during 2015 to Dec 2015
A75	2019	precision, recall, accuracy, Mean square error (MSE), Root-mean-square error (RMSE), Error rate	(EANN) accuracy: 99.93 (FFCM) -MSE: 0.079 (FFCM) - RMSE: 0.0691	NA	Crime Data From 2010 to 2019, Crime Incidents, Hate Crime Dataset and Annual Crime Dataset 2015
A76	2019	root mean square error (RMSE), coefficient of determination (R2), accuracy	accuracy: 77%	10-fold cross validation	NYC Open Data from 2015 to 2017
A77	2019	Hit rate, PAI (Personal Activity Intelligence), AUC	hit rate ratio: 24.6% - top 5% hotspot hit rate ratio: 60.4% - top 20% hotspot	5-fold cross validation	burglary incidents in the Swiss canton of Aargau from January 14, 2014 to January 13, 2017
A78	2019	accuracy	Larceny dataset: 0.79 Assault dataset: 0.82	NA	data about crimes from NYC Open Data
A79	2019	RMSE	RMSE: 0.28	NA	* real-time social media data from the Twitter API over six months * Open data Chicago crime data set from 2001 to 2018
A80	2019	*mean square error(MSE) * coefficient of determination (R^2) * root MSE (RMSE) * mean absolute error (MAE) * Directional accuracy (DA)	R^2: 0.98542 MSE: 0.00015 RMSE: 0.03836 MAE: 0.00990 DA: 0.96083	measurement criteria Davies-Bouldin Index (DBI) the Silhouette Index (SI)	* City of Chicago Crimes 2001 to 2019

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Table 13 (*continued*)

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
A81	2020	Root Mean Square Error (RMSE)	XGBoost RMSE: 0.4857	NA	* Points of Interest located in Fortaleza City from a web mapping service * Secretariat of Public Security and Social Defense dataset
A82	2020	* RMSE - Property Crime * MAE - Property Crime * Correlation - Property Crime * RMSE - Violent Crime * MAE - Violent Crime * Correlation - Violent Crime	* RMSE - Property Crime: 601.2 * MAE - Property Crime: 180.4 * Correlation - Property Crime: 0.82 * RMSE - Violent Crime: 1160.0 * MAE - Violent Crime: 346.1 * Correlation - Violent Crime: 0.81	5-fold cross validation	* Call Detail Records (CDR) from October 2009 to June 2010 * Mexico's Secretary General of National Public Security (SESNSP) property and violent crime data from 2011
A83	2020	* Precision * Recall * F-Measure (Macro-Averaged) * Accuracy * Micro-Averaged	(K-NN): * Precision: 0.912 * Recall: 0.85 * F-Measure (Macro-Averaged): 0.85 * Accuracy: 0.92 * Micro-Averaged: 0.895 (Random Forest): * Precision: 0.577 * Recall: 0.532 * F-Measure (Macro-Averaged): 0.51 * Accuracy: 0.62 * Micro-Averaged: 0.52	5-fold cross validation	archives of news data from the years 2011–2019
A84	2020	* RMSE * Rank Correlation	*assault RMSE: 14.797 Rank Correlation: 0.379 *Buglary RMSE: 8.899 Rank Correlation: 0.274	10-fold cross validation	Police Department Incidents Data Set in San Francisco from Jan 1, 2003 to Jun 25
A85	2020	* RMSE	RSME: 1.725265	NA	Chicago police data portal from January 1st, 2017 to December 31st, 2017
A86	2020	Average AUC	reported a lot of AUC for different cases * dimensionality reduction with attribute selection and with PCA * after transferring the model to test the AUC	k-fold cross-validation	* UK Police crime records * OpenStreetMap point of interest locations.
A87	2020	Adjusted-R^2 RMSE Accuracy	Extra-Trees: Adjusted-R^2: 0.81 RMSE: 0.013 Accuracy: 83%	Cross validation score	influence of 18 urban indicators within 6 categories
A88	2020	Hit rate PAI	Hit rate: 45.3% PAI: 3.43	NA	open data of 10 types of crimes happened in Chicago
A89	2020	RMSE Mean Square Percentage Error (MSPE) Jensen-Shannon Divergence (JS)	NA	NA	San Francisco government local police department records from 2003 till 2018
A90	2020	accuracy	78%	NA	Public Domain Data- National Crime Records Bureau.
A91	2020	Precision Recall Accuracy F-measure Time (Seconds)	Precision: 98.2 Recall: 98.1 Accuracy: 98.1 F-measure: 98.1 Time (Seconds): 7.24	10-fold cross-validation	crime tweets from the Twitter
A92	2020	Hit rate, Sensitivity analysis	12% in the mean hit rate at 10% coverage level and by 25% at 20% coverage level for burglary, assault and theft forecasting	NA	real-world crime data provided by the City of Chicago open data portal
A93	2020	* Predictive Efficiency Index (PEI) * Recapture Rate Index (RRI) * Predictive Accuracy Index (PAI)	NA	NA	NA
A94	2021	area under the curve (AUC)	accuracy: 76.4%	NA	public security bureau (PSB) from January 1to December 31, 2018
A95	2021	prediction performance (PR-AUC)	average PR-AUC: 0,3187 threshold: 0,168	cross validation error	data from 2007 to 2017 collected via the local police department from a large city in Belgium
A96	2015	Accuracy	NA	five-fold cross validate	* Foursquare data, * Gowalla data from Feb. 2009 to Oct. 2010 * San Francisco open crime activity data. till February 2015
A97	2016	sensitivity, specificity	Sensitivity: 79.24% Specificity: 68.2%	NA	Dhaka Metropolitan Police (DMP), records of reported crimes from June 2013 to May 2014
A98	2017	Correctly Classified Instances Kappa Precision ROC Area	varies for each crime type and each classifier	10-fold cross validation	Manila Police District (MPD) Office from the year 2012–2016
A99	2017	*PRECISION * RECALL *F1-SCORE	Recall: 87% Precision: 91% F1-score: 69%	NA	Smartphones and annotated by forensic expert (gold standard)

(*continued on next page*)

Table 13 (*continued*)

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
A100	2017	* Mean Squared Error (MSE) * Root Mean Squared Error (RMSE)	MSE: 0.00006996 RMSE: 0.0084	NA	City of Chicago Data Portal from January 2013
A101	2017	* Accuracy * Execution Time	Accuracy: 97% Execution time: 12 s	NA	* newspapers, e-papers, crime related records
A102	2019	* Correlation Matrix * Accuracy *F1 Score * unweighted average recall (UAR)	accuracy: 81.32 F1-score: 81 UAR: 81.47	NA	Chicago Crime Dataset from 2012 to 2019
A103	2019	*Validation Accuracy *Validation Loss	Accuracy: 100% Loss: 0.0031	NA	UCF Crime Data Set:
A104	2019	root mean square error (RMSE) Training Error Test Error Error in cumulated crime density Error in crime density	Training Error: 0.143 Test Error:0.207 Error in cumulated crime density: 0.750 Error in crime density: 0.659	cross validation	crimes recorded in LA over the last six months of 2015
A105	2019	Explained Variance Score (EVS) Mean Absolute Error (MAE) R Squared Score (R^2 Score)	EVS: 0.95 MAE: 2832 R^2 score: 0.95	NA	records from Bangladesh Police's website
A106	2019	*TP Rate *FP Rate *Precision *Recall *FMeasure *Time to Build the Model *Kappa Statistic *Mean Absolute Error *Root Mean Squared Error *Relative Absolute Error *Root Relative Squared Error *Prediction Accuracy	*TP Rate: 0.963 *FP Rate: 0.025 *Precision: 0.969 *Recall: 0.963 *FMeasure: 0.962 *Time to Build the Model: 0.32 *Kappa Statistic: 0.9322 *Mean Absolute Error: 0.0175 *Root Mean Squared Error: 0.0934 *Relative Absolute Error: 9.24% *Root Relative Squared Error: 30.91% *Prediction Accuracy: 96.34%	cross validation	Online scam unstructured data were considered as dataset containing a total of 14,098 mainly Filipino words
A107	2019	accuracy	Bagging: 99.92%	NA	crime datasets from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting)
A108	2019	*TP *FP *Accuracy *Precision *Recall	*TP 92% *FP 8% *Accuracy 92% *Precision 92% *Recall 100%	5-fold cross validation	data on Twitter' users, related to ISIS
A109	2019	*Accuracy *Precision *Recall *F1	*Accuracy: 0.948 *Precision: 0.948 *Recall: 0.948 *F1: 0.947	na	Global Terrorism Database(GTD), in 2015 and 2016
A110	2018	* MSE	RFR: 897.149	cross-validation	10 years of criminal records from 2 cities: San Francisco, US and Natal, Brazil
A111	2018	accuracy	between 39% and 44%	Cross-validation	Vancouver crime data for the last 15 years is analyzed using two different data-processing approaches
A112	2020	*Mean Absolute Error (MAE) *Mean Squared Error (RMSE) *TP Rate *FP Rate *Precision *Recall *F-Measure	*TP Rate: 0.721 *FP Rate: 0.207 *Precision: 0.721 *Recall: 0.721 *FMeasure:0.695 * Time to build: 212.36 * MAE: 0.059 * RMSE: 0.2181	CROSS-VALIDATION	data consisting of 54,059 mostly Filipino words as a significant continuation of a prior study
A113	2020	Demo, POI, -DI	1.5	NA	crime data set in San Francisco
A114	2020	* root-mean-square-error (RMSE) * Pearson Correlation Coefficient (PCC)	RMSE: 0.738 + 40.6% PCC: 0.879 + 8.9%	NA	*Crimes - 2001 to present *NYPD Complaint Data Historic
A115	2020	NA	NA	NA	crimes that has been happened in India from the year 2001
A116	2020	Confusion Matrix accuracy F1-score precision recall ROC curve	accuracy: 0.832 precision:0.845 recall: 0.895	NA	Baltimore Police Department's Victim Based Crime Data
A117	2020	MEAN Standard Deviation	MEAN:0.300385 Standard Deviation: 0.074799	cross validation	Vancouver Police Department (VPD) crime records from 2001 to 2012
A118	2019	NA	NA	NA	UCI and other sources
A119	2020	Correctly Classified Instances (CC), Accuracy (AC), Receiver Operating Characteristic Curve (ROC), Precision, and Recall	CC: 7763 AC: 91.59% ROC: 0.976 Precision: 0.926 Recall: 0.916	NA	incidents that occurred in the City of Chicago from 2013 to 2017 Chicago Police Department's Citizen Law Enforcement Analysis and Reporting (CLEAR)

(*continued on next page*)

Table 13 (*continued*)

ID	Year	Performance metrics	Metric and Value	Validation	Dataset
A120	2020	*Mean Absolute Error (MAE) *Mean Squared Error (MSE)	MAE: 0.4095 MSE: 1.4602	NA	crime data published by the Government of the Autonomous City of Buenos Aire from 2016 to 2019

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