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SURVEY

Artificial Intelligence in Crime Prediction: A Survey With a Focus on Explainability

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ABSTRACT Crime prediction has become a valuable tool for enhancing predictive policing, enabling law enforcement agencies to allocate resources more effectively and implement proactive crime prevention strategies, particularly in high-crime areas. The use of artificial intelligence (AI) has revolutionized this field by analyzing vast amounts of data to identify patterns and anticipate criminal activities with unprecedented accuracy. This paper aims to review the literature on AI-based crime prediction, analyzing 142 studies that focus on crimes against individuals, society, and property. Despite the promising potential of AI in crime prediction, significant challenges remain, particularly regarding the trustworthiness of AI systems, which is essential for their social acceptance. To address these issues, this review explores the explainability of AI-based prediction models, with a specific focus on the role of explainable AI (XAI). The findings highlight the importance of XAI in building trust in these models by offering more transparent and interpretable insights into how AI systems make decisions. However, the review also reveals that the integration of XAI remains underdeveloped in the current literature. By improving the transparency of AI systems, XAI has the potential to lead to more accurate, trustworthy, and fair crime predictions, ultimately facilitating more effective and equitable crime prevention efforts.

INDEX TERMS Crime prediction, artificial intelligence, explainability, interpretability, crime datasets, survey.

I. INTRODUCTION

Crime pattern theory encompasses four key dimensions: the law, the criminal, the target, and the location where the crime occurs [1]. Within this framework, the spatial and temporal distribution of crimes has been a significant area of focus, influenced by the routine activities of criminals and their engagement in structured patterns [1], [2].

Crime prediction methods and the analytical investigation of crime have gained increasing importance in recent years [3]. Predictive analytical approaches to determine where, when, and why crimes occur have also experienced significant growth [4]. The core principle of predictive modeling in criminology involves estimating how specific crime-related factors interact at a given time and place, leveraging predictive models to forecast future crime patterns and locations [5]. Furthermore, in criminal investigations, notable progress has been made in developing effective techniques to ensure consistent performance and deliver reliable, reproducible results from crime prediction models [6].

Artificial Intelligence (AI) has proven to be a fundamental tool in developing effective crime prediction systems. Today, AI-based systems enhance police awareness of existing and potential crimes, facilitate the resolution of complex cases,

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and support decision-making processes. These technologies have become integral to smart policing applications [7], [8], enabling law enforcement agencies to make informed decisions by efficiently analyzing vast amounts of crime data [9], [10], [11]. Furthermore, AI-based predictive analytics applications enable law enforcement agencies to optimize resource allocation and significantly reduce operational costs [12], while also having the potential to prevent crimes and to reduce crime rates [8], [13]. The effective use of crime prediction systems can further enhance police-public relations by alleviating safety concerns [14].

The recent development of AI, and in particular machine learning (ML), has made crime prediction tools significantly more accurate [15] and efficient [16]. However, while AI and ML technologies offer numerous benefits in criminal investigations, there is an urgent need for policies and regulations to govern their use [17]. It is essential to ensure that these technologies are applied ethically and responsibly. For instance, while these models are valuable, they can have limitations, particularly for disadvantaged groups [18]: they may reflect societal biases, leading to the unfair targeting of certain groups. This issue is well known and has led several governments to define laws and/or guidelines for developing trustworthy AI systems. A pioneering role in this context has been played by the ethics guidelines for Trustworthy AI produced by a group of high-level experts appointed by the European Commission, which defined fundamental principles to ensure ethics and responsibility in the use of AI [19]. Their framework outlines seven key principles to guide the design and implementation of AI technologies.

The first principle is transparency, which aims to address the "opaque box" problem by allowing users to understand and question AI decisions [19], [20]. This ensures that AI systems are not opaque and reinforces the second principle: accountability. Accountability requires developers, users, and organizations to take responsibility for the actions and decisions made by AI systems [21], [22], [23], [24].

The third principle emphasizes the need for AI systems to respect privacy and ensure the confidentiality of personal data [24], [25], [26]. The technical robustness and safety principle ensures that AI systems do not cause unintended harm, either physical or psychological, and that errors are detected and corrected to improve performance [25], [26].

The principle of human agency and oversight highlights the importance of enabling individuals to maintain control over AI systems and make independent decisions. This principle advocates for transparency in AI's functioning, ensuring users understand how decisions are made [19], [27]. The social and environmental well-being principle stresses that AI systems should contribute positively to society and environment, promoting sustainability [19].

Finally, the principle of diversity, non-discrimination, and fairness ensures that AI systems are free from biases and discrimination, ensuring fair treatment for all individuals, especially in sensitive areas like criminology, where equal access to justice and procedural fairness are paramount [19], [28], [29].

These principles are designed to create a framework that not only ensures AI systems are ethical and accountable but also that they operate in ways that benefit society as a whole, with a focus on fairness and sustainability. The importance of these principles is particularly evident in areas such as criminal justice, where AI's role must be handled with care to avoid biases and ensure fair treatment for all individuals involved in the process. Notably, these principles form the foundation of the European Union (EU) Artificial Intelligence Act, officially published on 12 July 2024. As the world's first comprehensive legal framework for AI regulation, it emphasizes the safe and rights-focused development and deployment of AI systems across the EU [30]. Similarly, other countries and organizations have adopted AI regulations. For example, the Organisation for Economic Co-operation and Development (OECD) updated its guidance on responsible AI in 2024, underscoring the importance of ethical AI governance [23].

Consequently, there is a growing emphasis on transparency and understandability in AI applications, particularly in policing and crime-related contexts [17]. Transparency is critical to building and maintaining public trust, especially in high-stakes domains like criminal justice, where the need for explainability [21], [31], [32], [33] and interpretability [34], [35] has intensified. When predictive models lack clarity, their legitimacy and reliability are undermined [36], [37]. Recent research on AI proposes methods on how to explain the functioning of AI systems, leading to fair and transparent decisions [20], [34], [38], [39].

This article aims to review recent AI-based approaches to crime prediction proposed in the literature, with a particular emphasis on explainability and interpretability. The study systematically examines commonly used datasets, the prediction techniques employed, and whether issues related to the transparency of these techniques have been addressed. Additionally, the study offers valuable insights for researchers by addressing potential challenges, issues, and research gaps related to explainable AI in crime prediction.

The rest of the article is organised as follows. Crime prediction approaches are presented in Section II. Explainable and interpretable AI and their impact on crime prediction are discussed in Section III. Section IV reviews recent survey studies on crime prediction. Our research methodology is presented in Section V. In Section VI, the research findings and results are discussed in detail. Section VII draws some conclusion and gives some suggestions for future research.

II. CRIME PREDICTION APPROACHES

Crime prediction systems encompass a range of methodologies designed to predict and prevent criminal activities, enabling law enforcement agencies to allocate their resources more efficiently. This section presents a comprehensive overview of the primary approaches and methodologies utilized in crime prediction. These approaches include Geographic Information System (GIS) and hotspot-based approaches, statistical-based approaches, ML-based approaches, and Deep Learning (DL)-based approaches.

A. GIS AND HOTSPOT-BASED APPROACHES

GIS and hotspot analysis are traditional methods used to visualize crime data on maps and identify areas with high concentrations of criminal activity [40]. These tools have become essential in crime analysis and prevention. With advancements in AI and the integration of GIS, crime mapping now enables law enforcement to allocate resources more effectively, engage in strategic planning, and implement proactive policing measures, contributing to improved public safety.

GIS were formally introduced in the early 1960s with the development of the Canada GIS, representing a major leap forward in digital mapping and spatial analysis. This innovation laid the groundwork for numerous applications of GIS in various fields, including crime prediction [41]. For example, areas with higher levels of poverty and fewer community resources have been found to have higher levels of violent crime. This correlation emphasises the need for comprehensive community development and crime prevention strategies [42]. Research indicates that wealthier neighborhoods tend to experience higher arrest rates for crimes, while disadvantaged areas see fewer arrests despite having similar crime rates. This disparity is attributed to the uneven distribution of police resources and variations in enforcement practices, raising concerns about systemic biases within law enforcement [43]. For more than a decade, predictive police software such as PredPol and CrimeScan have been using machine learning and GIS techniques to predict crime hotspots and help law enforcement in crime prevention.

Hotspot analysis, a statistical method for detecting areas of concentrated criminal activity, is a key tool in uncovering spatial patterns and designing targeted interventions [44], [45], [46]. Hotspot maps are also widely used in ML applications and have played a crucial role in policing practices [17], [47].

While GIS hotspot maps are instrumental in crime prevention, they often face criticism for being more descriptive than predictive [9]. Heat maps and hotspot maps, though frequently used interchangeably, serve distinct purposes: heat maps visualize data density, while hotspot maps reveal the statistical significance of data clusters, offering deeper insights for analysis [48]. GIS continues to play a vital role in crime prediction by identifying vulnerable communities, mapping high-risk areas, and analyzing the spatial distribution of crimes [44], [49], [50], [51], [52], [53], [54].

The integration of AI, ML, and DL with GIS has resulted in groundbreaking advancements in spatial analysis and geospatial intelligence, a field now commonly known as Geospatial AI (GeoAI). This convergence of technologies has transformed the way spatial data is analyzed, enabling more precise, efficient, and scalable insights into complex geospatial patterns and relationships [55].

B. STATISTICAL-BASED CRIME APPROACHES

Statistical methods have long played a crucial role in analyzing and predicting crime trends, offering foundational insights that have significantly influenced modern crime prediction techniques. While these methods are effective for temporal analysis and identifying trends over time, they often fall short in accounting for the spatial complexity of crime data.

Hybrid models that combine statistical methods with ML and DL have shown significant potential in enhancing prediction accuracy. By leveraging the strengths of the combination, these models can better capture complex patterns in crime data, improving the overall reliability of predictions [56], [57]. This enables law enforcement agencies to not only analyze and understand crime trends but also to predict future criminal activity with greater accuracy, thereby improving public safety and resource allocation [35], [56], [57], [58]. These studies have become a crucial tool for identifying areas at risk of crime and deploying tactical units effectively within these regions [59]. Among statistical techniques, AutoRegressive Integrated Moving Average (ARIMA) models are highly valued for their interpretability, which makes them particularly effective for applications like crime prediction. These models are known for their robustness and flexibility [35], [60], [61], providing clear insights into how past values influence future predictions, unlike many opaque "box" models used in ML [62].

Other than ARIMA, several other statistical techniques are widely used in crime prediction, each offering distinct advantages depending on the data and the analysis's specific goals. These techniques are Exponential Moving Average (EMA), Weighted Moving Averages (WMA), Simple Moving Averages (SMA), Kernel Density Estimation (KDE), Least Absolute Shrinkage and Selection Operator (Lasso), Ordinary Least Squares (OLS), Isotonic Regression and Support Vector Regression (SVR). Each method serves a different purpose and exhibits unique features that make it a valuable tool in crime prediction.

C. ML-BASED APPROACHES

ML plays a pivotal role in modern data analytics and data science, driving the creation of more intelligent systems and applications. As data expands in scale and intricacy, ML models must adapt accordingly to sustain their performance and deliver valuable, relevant analyses [63]. This constant evolution ensures that ML systems remain capable of extracting meaningful patterns and insights from dynamic datasets [64]. Despite the advancements and high prediction accuracy achieved by ML algorithms, interpretability is a significant concern, particularly when these models are used in sensitive areas like crime prediction [65], [66].

ML has emerged as a pivotal tool in crime analysis, especially from the 2000s onward, marking a significant shift from the traditional statistical methods prevalent in the 1990s. This integration of ML has revolutionized crime prediction research by enabling more timely and accurate forecasts regarding crime locations and timings [67].

There has been a growing body of research incorporating both temporal and spatial variables derived from spatial data in prediction models using ML techniques, as these factors influence the repeatability of crimes [68], [69]. While traditional models are effective at clarifying the relationships between variables and their impact on crime patterns, ML methods offer distinct advantages, often resulting in more precise and reliable crime predictions [17], [70].

The most popular methods used in crime prediction are Linear Regression (LR) and Logistic Regression (LogReg), Decision Tree (DT), ensemble learning models, such as Random Forest (RF) and Gradient Boosting (including XGBoost, AdaBoost, LightGBM, and CatBoost), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) [67], [71], [72].

Choosing the appropriate method depends on the specific requirements of the crime prediction task, including the need for accuracy, interpretability, and computational efficiency. DTs and regression algorithms (LR and LogReg) are frequently preferred and widely used methods in crime prediction due to their simplicity and interpretability [73], [74].

D. DL-BASED APPROACHES

DL is a specialized branch of ML that leverages artificial neural networks with multiple layers, commonly known as deep neural networks (DNNs), to analyze and extract insights from large, complex datasets [75]. These networks are designed to automatically learn hierarchical representations of data, enabling them to perform tasks such as pattern recognition, image classification, and predictive modeling with remarkable accuracy. However, their intricate structure often makes them difficult to interpret, contributing to their "opaque box" nature. Overcoming this challenge requires employing explainability techniques, simplifying models where feasible or using post-hoc explanations to better understand how the models make decisions [33], [76], [77], [78]. Striking a balance between the computational power of deep learning and the need for transparency is essential to ensure its responsible and effective use in applications such as crime prediction [75], [79].

The primary DL models applied in crime prediction are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory Network (LSTM), Multilayer Perceptron (MLP).

DL models have been applied to various crime prediction tasks, such as predicting crime hotspots and crime rates, and identifying high-risk individuals [80]. However, the success of these approaches depends on the availability of high-quality crime datasets and the ability to incorporate domain knowledge into the model design [81]. This ability is particularly valuable in understanding crime trends and predicting future events. In the field of crime prediction, combining ARIMA with ML and DL approaches has been an innovative strategy to leverage both traditional statistical methods and advanced computational techniques. This hybrid approach aims to improve the accuracy and robustness of crime forecasts by integrating the strengths of different techniques [35], [56], [57], [58].

III. EXPLAINABLE AI (XAI)

As AI has proliferated across several sectors, including marketing and the military, the necessity to explain how a system works and why a certain decision is proposed has become increasingly relevant. Currently, there is not an established and unique definition of explainability in the literature, probably due to the presence of different stakeholders with different domain expertise. However, in an attempt to establish a common definition, we can refer to XAI as the research field focused on explaining to relevant stakeholders how an AI-based system functions and the reasons behind the specific output(s) it generates. Among its many benefits, XAI simplifies the understanding of an AI system's errors, allowing for corrections and improvements while reducing biases, and helps stakeholders better understand the decisions made by the system. In fact, explainability is crucial for enhancing the trustworthiness of AI, not just for end-users, but also for all involved parties. This trust is especially important in systems where life-impacting decisions are made, such as those used in crime prediction.

There are two main methodologies to address the explainability requirement in AI systems [20], [82]: the exploitation of interpretable by-design models and the application of post-hoc (explainability) techniques.

Interpretable-by-design models (also referred to as *ante-hoc*, intrinsically explainable, transparent, glass-box models or glass-box models) are those models that are designed in a way that is "immediately understandable by humans" [82]. Here, understandability is referred to as "*the characteristic of a model to make a human understand its function (that is, how the model works) without any need for explaining its internal structure or the algorithmic means by which the model processes data internally*" [82]. Thus, in this context the concept of understandability is related to the cognitive skills and to the previous knowledge of the stakeholder involved.

This category typically encompasses models such as: i) case-based reasoning models, like KNN, ii) logic-based models, such as DTs or fuzzy rule-based systems, iii) linear/logistic regression, iv) generalized additive models, and v) Bayesian models. For these types of systems, the rationale behind the outcomes is generally easy to comprehend. For example, a list of *if-then* rules can be extracted from a DT, following the paths from the root to each leaf containing the system's decisions.

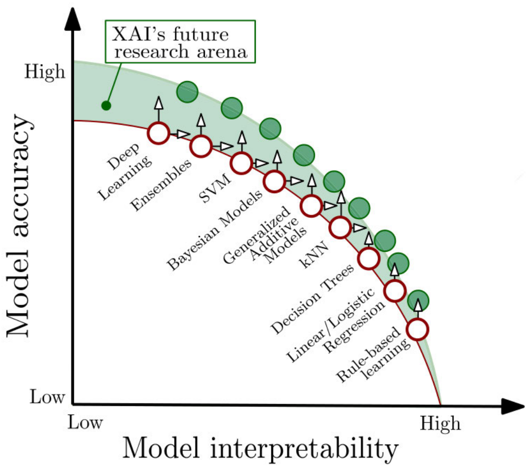

FIGURE 1. **Tension between model interpretability and performance, extracted from [82].**

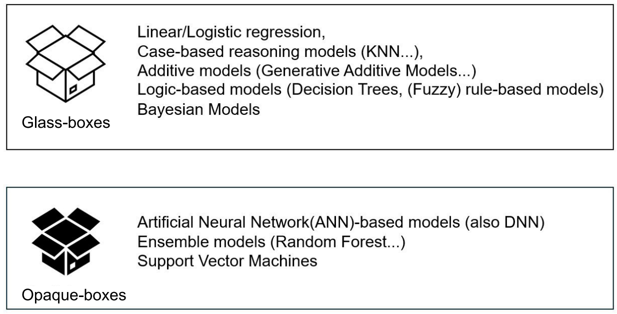

FIGURE 2. **XAI models taxonomy.**

Post-hoc methods aim to explain why a model provides a decision after the decision is made (hence the name). Usually, these methods are applied to the decisions of those AI systems referred to as "opaque models" or "opaque boxes". Schematically, we can refer to opaque box models as those models that have a more complex and opaque structure with respect to the interpretable by design models, making difficult to understand how the inputs are transformed into the decisions: as a matter of fact, they have been designed with the primary objective of achieving high accuracy. For this reason, models such as ensemble models, Support Vector Machines or models based on Neural Networks are usually referred to as opaque box models. Figure 2 reports a list of glass and opaque boxes, following the taxonomy in [82]. Since the advent of XAI, several post-hoc methods have been proposed in literature with different characteristics and addressing specific challenges. The following Subsection III-A reports details on the different methods.

Notably, the literature discusses a tension between accuracy and explainability/interpretability. The underlying notion is that opaque box models may provide superior performance due to their complexity, making them better suited to model complex realities. However, for the same reason, they tend to be more difficult to understand. This tension is widely discussed in [36] and [82], and is often depicted as shown in Fig. 1. However, the literature also underlines how this tension depends on the complexity of the problem considered: if the relationship between input and output is easy to model, if the number of features is small, or the dataset size is limited, the performance of complex and simple models should not differ significantly.

Finally, it is worth noticing how several terms such as interpretability, transparency and explainability are often used interchangeably, even if they have different nuances of meaning. We refer to [82] for a more detailed discussion on the taxonomy.

A. POST-HOC METHODS

The post-hoc methods are generally categorized in various ways, depending on the perspective taken into consideration. A fundamental distinction is made based on the strategies employed for providing explanations, which mirror the different ways humans explain things in everyday life. From this perspective, post-hoc methods can be schematically divided into the following categories: i) explanations based on the importance of the features (referred to as feature importance or relevance), ii) rule-based explanations, iii) prototype explanations, iv) contrastive/counterfactual explanations, and v) textual or visual explanations [20], [82].

Considering their relationship with the AI-models, the group of post-hoc methods designed to address specific models are referred to as *model-specific*, while the ones that can be applied to every model are called *model-agnostic* [83]. Furthermore, there are techniques tailored for specific kind of data (tabular, text, image, time series, graphs) as schematized in [83]. Feature importance and rule-based explanations are often used for tabular data, while saliency maps (the equivalent of feature importance) and concept attribution are commonly used for images. In addition, a distinction can be made between *local* and *global* explanations: the former refers to the inference process and provides an explanation for why a particular decision was made. The latter aims to describe the global behavior of the system, for example by providing aggregated information evaluated over an entire dataset. In this sense, global explanations can be related to the structure of the model [84].

Finally, there are techniques tailored to specific types of data, such as tabular, text, image, time series, and graphs, as schematized in [83]. Feature importance and rule-based explanations are commonly used for tabular data, while saliency maps (the equivalent of feature importance) and concept attribution are typically used for images.

Arguably, the most commonly used post-hoc methods are SHAP and LIME. Both are model-agnostic and local explanation methods. SHAP (SHapley Additive exPlanations) [85] provides explanations in terms of the importance of the singular input feature to the final decision. It has a strong mathematical foundation, being based on the game theoretically optimal Shapley values. Given a model m and an input instance i, SHAP explains the prediction $m(i)$ by computing the contribution of each feature to the prediction. By construction, it is a local method, but it can also be used as a global method after the evaluation of all the individual explanations accross the entire dataset.

LIME (Local Interpretable Model-agnostic Explanations) takes a different approach, based on the intuition of approximating the behavior of the AI system with a simpler, more understandable model to explain each individual decision. This simpler model, referred to as the *surrogate* model, is typically a model interpretable by design (e.g.: a linear model or a DT). In detail, given a model m and an input instance i, LIME explains the individual decision $m(i)$ via the following steps: i) a perturbed (synthetic) sample close to i is created ii); for this sample, the predictions of the model m are computed; iii) the predictions and the synthetic data sample are used to train the surrogate model s; iv) finally, the explanation of the individual decision $m(i)$ is given by interpreting the surrogate model s.

Both SHAP and LIME are used for different kinds of data (tabular, images, or textual data).

IV. RELATED LITERATURE

In this section, we summarize some recent reviews providing insights into the application of ML and data mining (DM) techniques to predict various types of crimes, offering valuable perspectives on the methodologies and results from recent research in this area.

A review conducted in 2018 [86] explored the use of DM and ML techniques in crime prediction, covering crime categories such as fraud, violent crime, traffic violence, sexual assault, and cybercrime. The review analyzed eight articles and datasets, categorizing crime types and summarizing data descriptions and sources. It highlighted the use of classification and clustering techniques for predicting violent crime and sexual assault, offering valuable insights into emerging methodologies in crime prediction.

In 2020, a review [87] focused on ML techniques for recognizing crime features, with an emphasis on the influence of socioeconomic, cultural, and demographic factors on crime characteristics. The review analyzed 15 papers, comparing the techniques, advantages, and limitations. It recommended adapting ML and DL approaches to the specific characteristics of crime data and advocated for the use of feature-based models in predictive policing and legal decision-making.

Another review [88] in 2020 analysed crime prediction techniques for spatio-temporal hotspot detection, covering 49 research papers published between 2010 and 2019. The study emphasized the importance of big data and the accuracy of DM and ML techniques. It classified crime prediction methods under spatio-temporal analysis, hotspot detection, and crime mapping. The most accurate techniques were found to be DBSCAN and RF, with the study proposing the use of DBSCAN clustering for hotspot detection and ARIMA time series for crime prediction.

A 2022 review [89] analyzed 16 papers exploring neural networks, statistical methods, and spatio-temporal approaches for predicting crime events. The study found that standalone models, such as basic neural networks or CNNs, struggled to achieve high accuracy. However, when combined with other models, their performance improved significantly. In particular, the study highlighted that LSTM networks and regression modeling achieved superior prediction results, with an average accuracy of 90%, closely aligning with real-world scenarios. The study highlighted the importance of incorporating both temporal and spatial data to improve prediction accuracy.

Another 2022 review [9] examined AI-based crime prediction using ML and DL techniques. It analyzed 120 research papers published between 2008 and 2021, finding that supervised learning was the most commonly applied ML method. The study noted that robbery was the most frequently studied crime type, with RF and Naïve Bias (NB) being the most widely used algorithms. Datasets from Chicago, India, and the USA were frequently employed, with Weka, Python, and R being the most common tools used.

In 2023, a review [72] focused on the datasets and prediction techniques employed in crime prediction research, with an emphasis on ML and DL methods. The study highlighted that CNN-based models generally outperform traditional ML approaches in crime prediction, with datasets from the USA and India being the most common. Among the most frequently applied algorithms were DT, SVM, RF, AdaBoost, and NB. The review also noted that interpretability remains a significant challenge in DL models, calling for greater transparency in how these models make predictions. The study suggested that building models with a solid theoretical foundation would not only provide clearer explanations for the algorithm's decisions but also pave the way for future research in which visualization tools could be used to present each step of the model more clearly.

Another review in 2023 on temporal and spatial crime prediction [60] analyzed 79 articles published between 2013 and 2022, identifying RF and LogReg as the most commonly used techniques. Artificial Neural Networks (ANNs) were preferred for medium-term predictions, while ARIMA models and ensemble learning were more common for long-term forecasts. The study recommended the use of transfer learning to address data sparsity and improve the adaptability and performance of crime prediction models in real-world environments. It also emphasized the importance of model interpretability and the use of techniques like SHAP for post-hoc explanations.

Also in 2023, in a review by [90], the potential of ML techniques to improve crime prediction accuracy was highlighted. The study summarized seven articles, focusing on techniques such as LogReg, DT, RF, and SVM. It stressed the role of ML in identifying crime trends and real-time prediction, with datasets from cities like Chicago, London, New York, and Philadelphia being commonly used.

A further review in 2023 by [81] synthesized research between 2018 and 2022, emphasizing the benefits of both ML and DL techniques. It involved a comprehensive review of various scientific databases, selecting 51 articles from a pool of 157 for evaluation. The literature was analyzed in terms of crime type, location, ML techniques used, datasets, and prediction performance, with detailed tables summarizing these aspects. The study identified the Los Angeles crime dataset as the most commonly used, followed by datasets from New York and Philadelphia. Hybrid techniques and natural language processing (NLP) were also noted as being useful for classification tasks in neighborhood crime studies. The review stressed the importance of incorporating cause-and-effect relationships between variables in predictive models and suggested further exploration of the ethical implications of using ML and DL in crime prediction.

In the most recent review [67], the study highlighted the challenges in crime prediction between 2010 and 2022, based on 68 selected ML articles. It found that labeled data is often unavailable in real-world scenarios, which complicates model training. The study identified DT-based techniques, such as RF, DT, Extra Trees, and Gradient Boosting, as the most effective for crime prediction. It also emphasized the role of big data, feature selection, and supervised learning in enhancing prediction accuracy. Public datasets were the most commonly used, with accuracy being the primary evaluation metric.

Table 1 provides a summary of the key characteristics of the review articles discussed above. It outlines the databases consulted for searches, the specific query used, the time period covered, the number of papers analyzed, the prediction techniques adopted in the works discussed in the papers, the types of crimes examined, the datasets utilized (with links where available), and the extent to which explainability aspects are considered.

This review comprehensively examines the literature on crime prediction studies utilizing AI technologies up to May 2024. It provides a broader scope and updates the foundational information covered in previous studies, offering a detailed synthesis of advancements in the field. The unique contributions of this research, which distinguish it from prior reviews, are summarized below:

- **Support for Stakeholders:** This review serves as a valuable resource for governmental institutions, particularly law enforcement agencies, as well as researchers and private organizations. It synthesizes the entirety of crime prediction studies using AI technologies, highlighting advancements, challenges, and emerging opportunities in the field.
- **Addressing Gaps in Explainability:** The study fills critical gaps in the existing literature by focusing on the often-overlooked aspect of explainability in crime prediction models.
- **Evaluation of Prediction Models:** Existing prediction models are thoroughly summarized and discussed, with suggestions for improvements aimed at enhancing the fairness, transparency, and accountability of ML prediction techniques.
- **Data Accessibility and Comparison:** By distinguishing between private and public data portals used in criminal investigations, the review identifies the most effective datasets for prediction models.
- **Explainability Techniques:** The research contributes to future studies by reporting on explainability techniques, categorizing them into ante-hoc/post-hoc, local/global, and specific/agnostic approaches, thus paving the way for more interpretable and trustworthy prediction results.

V. RESEARCH METHODOLOGY

In our review, we utilized the Scopus database, recognized as one of the world's most comprehensive repository of scientific literature abstracts and citations, offering extensive global and regional coverage. We used the search query: 'crime prediction' AND 'artificial intelligence' OR 'crime prediction' AND 'machine learning' OR 'crime prediction' AND 'deep learning', 'crime prediction' AND 'explainable AI' and 'crime prediction' AND 'interpretability'. We limited our research to recent papers published from January 1, 2015. The search yielded a total of 660 publications until May 1, 2024.

We focused on the following categories of crimes as identified by the NIBRS system (National Incident-Based Reporting System) [91]:

- crimes against persons: burglary, homicide, human trafficking, kidnapping, sex offenses;
- crimes against property: burglary, motor vehicle theft, fraud and robbery;
- crimes against society: Drug/narcotic.

Further, papers written in languages other than English were excluded from the review. After the selection process, 142 articles remained, which are described in Table 2. For each paper, the table presents the reference, the type of crime addressed, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset source, and, if available, the dataset link(s).

Figure 3 illustrates the yearly distribution of publications using AI technologies in crime prediction from 2015 to May 1, 2024. The data reveals a growing interest in AI in recent years.

The research methodology consists of two stages. The first stage aims to uncover valuable information about the datasets used in crime prediction research, including their sources and accessibility (public or private). The second stage focuses on analyzing studies that utilize different AI approaches for crime prediction, specifically assessing explainability. These studies are classified based on ante-hoc/post-hoc and local/global explainability approaches to ensure that AI systems' decision-making processes are comprehensible.

TABLE 1. Related review studies.

Ref.	Databases	Query	Years	Number of papers	Prediction techniques	Crime Type	Datasets and links	Explainability aspects
[86]	No	No	No	8	DM, ML	Fraud detection, Violent, Traffic violence, Sexual assault, Cyber crime	8	No
[87]	No	No	No	15	DM, ML, Trans.Lear.	No	No	No
[88]	IEEE, Science Direct, Springer, Scopus, ACM	"Spatio OR Spatial OR Spatio-temporal OR Temporal OR Spatial and Temporal) AND (Crime OR Violation) AND (hotspot OR Dense) AND (Identification OR Detection OR Forecasting OR Prediction) AND (Data mining OR Machine learning)	2010-2019	49	Hotspot dedection (HD)	Larceny, assault, harassment, burglary, rape, robbery, sex crimes, drug etc.	8, No link	No
[89]	No	No	No	16	Stat., NN, Spatiotemporal approaches	All crimes	No	No
[9]	Google Scholar and Scopus, Springer, IEEE Explorer, ACM, Elsevier	"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"	2008-2021	120	DM, ML	Robbery, Theft, Burglary, Rape, Vandalism, Assault, Trafficking, Murder/Homicide	No	Yes
[72]	No	No	No	No	ML, Hotspot Analysis, DL	No	Yes (No link)	Yes
[60]	WOS, IEEE, ACM	Crime prediction, predict crime, crime forecasting, forecasting crime, spatio-temporal crime prediction, spatial crime prediction, and temporal crime prediction."	2013-2022	79	ML, Crime mapping	Theft, burglary, assault, battery, robbery, homicide, narcotics, other	No	Yes
[90]	No	No	No	7	DM, ML	No	No	No
[81]	IEEE, Science Direct, ACM	(("Document Title": "crime*") AND ("Document Title": "predic*" OR "Document Title": "detec*" OR "Document Title": "recogni*" OR "Document Title": "machine learning" OR "Document Title":"deep learning" OR "Document Title":"clustering" OR "Document Title":"natural language processing"))	2018-2022	51	ML, DL	No	Yes	Yes
[67]	ACM, IEEE, Springer, Science Direct, Scopus	"Crime", "crime prediction", and "machine learning"."Neural Networks", "Artificial Intelligence", "Data mining" and/or "Crime patterns"	2010-2022	68	ML, supervised machine learning approach	No	Yes (Private/Public)	No
Our study	Scopus	*"Crime prediction" AND "artificial intelligence" OR "crime prediction" AND "machine learning" OR "crime prediction" AND "deep learning", "Crime prediction" AND "Explainable artificial intelligence" and "crime prediction" AND "interpretability"*	Until May 2024	142	HS, Stat., ML, DL	All crime types against persons, property and society	Yes (Private/Public)	Yes

VI. ANALYSIS AND DISCUSSION OF THE RESULTS

In this section, we provide a detailed discussion of the results of our research. First, we analyze the datasets used in crime prediction across three aspects: the type of crime, the provenance of the data, and the type of access (public or private). Next, we examine the approaches, focusing on the objectives of the papers, the prediction techniques, and model explainability.

A. ANALYSIS OF DATASETS USED IN CRIME PREDICTION

In this subsection, we analyse some aspects of the datasets used in crime predicition. The first aspect is related to the types of crime investigated in the papers in Table 2. Figure 4 shows the distribution of the papers based on crime types. Theft emerges as the most frequently studied crime type, accounting for 15.35% of the total. Similarly, robbery constitutes 13.02%, and assault represents 10.23%. These primary crime types are followed by burglary (9.53%), violence (6.74%), drug-related crimes (6.76%), murder (4.42%), larceny (4.90%), homicide (3.95%), kidnapping (3.72%), sexual offenses and rape (3.49%), damaged property (2.79%), battery (2.56%), and weapons-related crimes and dacoity (1.63%). Less commonly studied crime types include arson (1.40%), vandalism (1.16%), pickpocketing (0.93%), and other offenses such as women and child repression, shoplifting, harassment (0.70%), and child abuse (0.47%). These findings highlight the focus of crime prediction research on theft, robbery, and assault while underscoring the potential for further exploration of less frequently analyzed crime types.

The second aspect pertains to the provenance of the data, specifically the country and, where available, the city. As illustrated in Figure 5, crime data from the United States, including general and city-specific datasets, dominate the field, accounting for 60.0% of the datasets used in these studies. This is followed by datasets from India (7.78%), China and Brazil (3.33% each), and Colombia (2.22%). Notably, public datasets from the US and India are being increasingly leveraged for crime prediction, employing a wide range of ML techniques [35]. These datasets have become pivotal in advancing the development of more accurate and robust crime prediction models, driving innovation in this field. Figure 6

TABLE 2. Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).

Nu.	References	Type of crime	Dataset Description	Public/ Private Dataset(s)	Source	Dataset Link(s)
1	[92]	Violent crime	Combination of socioeconomic data from the 1990 USA census, law enforcement data from the 1990 Law Enforcement and Administrative Statistics survey, and 1995 FBI UCR crime data	Public	UCI	https://archive.ics.uci.edu/dataset/211/communities+and+crime+unnormalized
2	[93]	General and violent crime	Arrest and Compas	Public	NLSY97 and Compas	https://www.bls.gov/nls/, https://www.propublica.org/datastore/dataset/compas-recidivism-risk-score-data-and-analysis
3	[94]	Grand larcenies, burglary, assault, robbery	NYC (2011–2015)	Public	NYC Open data	https://opendata.cityofnewyork.us/
4	[95]	Violent crime	Combination of socioeconomic data from the 1990 USA census, law enforcement data from the 1990 Law Enforcement and Administrative Statistics survey, and 1995 FBI UCR crime data	Public	UCI	https://archive.ics.uci.edu/dataset/183/communities+and+crime
5	[96]	Theft, battery, narcotics, criminal damage, assault, burglary, robbery, weapons violation, sex offence etc.	Chicago, Illinois (2014)	Public	-	https://data.cityofchicago.org/
6	[97]	Drug related crime, fraud, assault, intimidation, auto theft, burglary	Recorded data (undefined)	Private		-
7	[98]	Carnapping, gun shooting, homicide/murder, physical injury, robbery/theft, sexual abuse	Manila Police District (MPD) Office (2012-2016)	Private	-	-
8	[99]	Homicide	Brazilian Public Health System, DATASUS (2000)	Private		
9	[100]	Theft (Electric bike)	Pekin/China (2008 -2014)	Private	-	-
10	[101]	Alcohol-related, assault, property crime(theft, robbery), vehicle crime	Canada/Halifax (2016)	Private	-	-
11	[12]	Theft, burglary, criminal damage, drugs, vehicle crime	U.K. (2015-2017)	Public	U.K. Crime data	https://data.police.uk/data/
12	[102]	Undefined	Chicago (2001-2018)	Public	-	No Links
13	[103]	Theft	Vancouver crime data, Canada (2003-2018)	Public	-	https://vpd.ca/crime-statistics/
14	[104]	Robbery, burglary, misdeed, violence etc.	Poland Police and LEA agencies, project PROKRYM, undisclosed police records (2008-2014)(2013-2016)	Private	-	-
15	[105]	Burglary, theft	Taoyuan City, Taiwan (2015-2016)	Public	-	https://data.gov.tw/
16	[31]	Low impact crimes, homicide, kidnapping, violation, injuries by firearm shot	Tabular/public crime database/Mexico City (January 2016 to March 2019)	Public	-	https://datos.cdmx.gob.mx and www.worldweatheronline.com
17	[106]	Sexual offenders	Chicago dataset	Public	Chicago data portal	https://data.cityofchicago.org/Public-Safety/Crimes-2022/9hwr-2zxp/data
18	[107]	Undefined	Natal, Brazil	Private	-	-
19	[46]	Burglary	Swiss canton (January 14, 2014-January 13, 2017)	Private	-	-
20	[15]	Murders	NYPD (2017-2018)	Public	NYPD	No Links
21	[108]	Assault, larceny/theft, prostitution, sexual offenses, drug/narcotic, burglary etc.	San Francisco (2003 to 2018)	Public	SFPD	https://data.gov/open-gov/

TABLE 2. *(Continued.)* **Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).**

22	[109]	Threaten, protest, coerce, assault, fight, violence	Saudi Arabia (from January 1 2018 to September 23 2018)	Public	GDELT	https://www.gdeltproject.org/
23	[110]	Undefined	NCIC - National Curriculum Information Center, Korea (1997-2017)	Private	-	-
24	[111]	Undefined	Atlanta (2009-2016)	Public	-	No Links
25	[112]	Robbery, assault	Kobe city, Japan (2016-2017) / Boston city, USA (2012-2015)	Public	- / Boston Police Department	- / https://data.boston.gov/dataset/crime-incident-reports-august-2015-to-date-source-new-system
26	[61]	Homicide, criminal sexual assault, robbery, battery, public peace violation, assault, burglary, theft, arson, human trafficking, sex offence, kidnapping, narcotics	Chicago (2001)	Public	Chicago data portal	https://data.cityofchicago.org/
27	[113]	Assault, burglary, homicide and narcotics	Chicago (2001)	Public	Chicago data portal	https://data.cityofchicago.org/
28	[114]	Arson, assault, battery, burglary, sexual assault, homicide, theft, robbery,	Chicago (from 2002 to 2017)	Public	Chicago data portal	https://data.cityofchicago.org/
29	[115]	Arson, assault, drugs, homicide, kidnapping, robbery, sexual offence, theft, weapons offence	Cheltenham, UK (1/1/2017-2/1/2017)	Private	-	-
30	[116]	Theft, assault, damage property, warrants, kidnappings, robbery	San Francisco (1/1/2003 - 5/13/2015)	Public	San Francisco open dataset	https://datasf.org/opendata/
31	[117]	Robbery, theft	UOF dataset, Brazilian government (from January 2012 to November 2017)	Private	-	-
32	[118]	Larceny, burglary, theft, robbery, shooting, Homicides, violent, arson,rape, assault	Baltimore, Maryland state of USA (from January 2016 to December 2018)	Public	-	https://homicides.news.baltimoresun.com/ https://data.baltimorecity.gov/Public-Safety/BPD-Part-1-Victim-Based-Crime-Data/wsfq-mvij
33	[119]	Undefined	Saudi Arabia (No date)	Private	-	-
34	[120]	Theft, robbery, snatching and other types	Coastal city in the southeast of China (2015-2018)	Private	-	-
35	[121]	Assault, larceny/theft, robbery, etc.	San Francisco Police Department	Public	-	https://datasf.org/opendata/
36	[122]	General	San Francisco city dataset (2003-2015)	Public	Kaggle	https://www.kaggle.com/competitions/sf-crime/data
37	[123]	Violence, burglary, shoplifting, theft, robbery,	Police crime records for selected UK	Public	-	https://figshare.com/articles/dataset/Data_and_source_code_for_crime_prediction_based_on_POI_locations_Manchester_Liverpool_Bournemouth_Wakefield_/11662359
38	[124]	Undefined	San Francisco (2011-2015)	Public	-	https://datasf.org/opendata/
39	[125]	Violent crime	Lagos, Nigeria, (from June 2014 to June 2019)	Private	-	-
40	[126]	Pickpocketing, violence, theft	undefined	Private	-	-
41	[127]	Undefined	Chicago Police Department (2019); Los Angeles - Police Department (2019)	Public	Chicago Data Portal	https://data.cityofchicago.org/

TABLE 2. *(Continued.)* **Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).**

42	[128]	Robbery	City of Fortaleza, Brazil (2015-2019)	Private	-	-
43	[129]	Violent, property crime, vandalism, motor vehicle theft	Crime Open Database, USA (Tucson, AZ; Los Angeles, CA; San Francisco, CA; Chicago, IL; Louisville, KY; Detroit, MI; Kansas City, MO; New York, NY; Austin, TX; Fort Worth, TX; and Virginia Beach, CA)(2018-2019)	Public	-	https://osf.io/zyaqn/
44	[130]	Robbery, assault, grand larceny and criminal mischief	NYC Open Data (from January 1, 2014 to December 31, 2014)	Public	-	https://opendata.cityofnewyork.us/
45	[131]	Home burglary	Belgian city's police department(2012-2017)	Private	-	-
46	[132]	Theft and robbery	ZG City, China (2 January 2017 - 3 December 2017)	Private	-	-
47	[133]	Theft, theft from the person, bicycle theft, violence and sexual offences, shoplifting, drugs, criminal damage and arson, burglary, public order, vehicle crime, other crime, possession of weapon and robbery.	Chicago Crime Data (2014-2015)	Public	-	https://data.cityofchicago.org/
48	[134]	Homicide, theft, robbery	Ministerio de Justicia y Seguridad. Policía de la Ciudad , Buenos Aires (2016-2019)	Public	-	https://data.buenosaires.gob.ar/dataset/delitos
49	[135]	All crimes	New York City (NYC) (2008-2017)	Public	-	https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Histori%c/qgea-i56i/data
50	[136]	Murder, assault, dacoits, theft, kidnapping, robbery	NCRB, all states in India (2001-2015)	Public	-	https://data.gov.in/ministrydepartment/National%20Crime%20Records%20Bureau%20(NCRB)
51	[137]	Weapon violence, theft, sex offenses, robbery, narcotics, assault, arson, battery, homicide	Chicago; Los Angeles	Public	-	https://data.cityofchicago.org/stories/s/Crimes-2001-to-present-Dashboard/5cd6-ry5g; http://egis3.lacounty.gov/dataportal/?s=crime.http://egis3.lacounty.gov/dataportal/?s=crime.
52	[138]	Theft, assault, murder, robbery, sexual offenses	South Africa (2005–2016)	Public	Kaggle	https://www.kaggle.com/datasets/slwessels/crime-statistics-for-south-africa
53	[139]	Theft, assault, murder, kidnapping, rape, robbery, shoplifting	South Bangalore (2020)	Public	Kaggle	https://www.kaggle.com/vineetsingh26/bangalore-south-crime-detail.
54	[76]	Larceny/Theft, assault	San Francisco Police Incident Report (SFPIR) (from January 1, 2003 to May 15, 2018)	Public	-	https://datasf.org/opendata/
55	[140]	Undefined	LA Crime dataset	Public	-	https://data.lacity.org/A-Safe-City/
56	[141]	Theft-related crime data	New York City Open Data (from January 2010 to 31 December 2015)	Public	-	https://opendata.cityofnewyork.us/

TABLE 2. *(Continued.)* Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).

57	[142]	Dacoity, robbery, murders	Bangladesh Police departments (2010-2018)	Public	Github	https://github.com/pavstar619/NahidSir_prototype_bdpolice_V2
58	[143]	Assault, pickpocketing, snatching	City of Medellin, Colombia (from January 1, 2015 to October 31, 2019)	Public	-	https://medata.gov.co/dataset/hurto-persona.
59	[144]	Theft, narcotics, burglary, weapons violence, battery, assault, robbery, criminal damage	Chicago (2017-2020)	Public	Chicago Data Portal	https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2.
60	[145]	Theft, narcotics, burglary, weapons violence, battery, assault, robbery, criminal damage	Chicago (2017-2020)	Public	Chicago Data Portal	https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2.
61	[146]	Arrest (general)	Chicago (2001-2020)	Public	-	https://data.cityofchicago.org/stories/s/Crimes-2001-to-present-Dashboard/5cd6-ry5g
62	[147]	Assault, theft, robbery, burglary, homicide, narcotic	Seattle(1996-2016), Minneapolis (2010-2016), Philadelphia (2006-2017), San Francisco (2003-2015), Metropolitan DC (2008-2017)	Public	Kaggle	https://www.kaggle.com/samharris/seattle-crime; https://www.kaggle.com/datasets/mrisdal/minneapolis-incidents-crime; https://www.kaggle.com/datasets/mchirico/philadelphiacrimedata;https://www.kaggle.com/c/sf-crimedatasets/; https://www.kaggle.com/vinchinzu/dc-metro-crime-data
63	[148]	Robbery	Dallas (from June 2016 to May 2018)	Public	-	https://www.dallasopendata.com
64	[77]	Robbery	Bogota, Colombia (2016–2019)	Private	-	-
65	[149]	Theft, vehicle-related theft	South Korea/ Dongjak (2004-2015)	Private	-	-
66	[150]	Dacoity, robbery, murder, speedy trial, riot, women child repression, kidnapping, police assault, burglary, theft, other cases	Bangladesh Police dataset (2010-2019)	Public	-	https://www.police.gov.bd/en/crime_statistic/year/2019
67	[151]	Homicide	Metropolitan Police of Bogotá, Colombia (2018-2019)	Private	-	-
68	[152]	Murder, homicide, rape, theft, robbery, kidnapping, dacoity	NCRB, India (2001-2012)	Private	-	-
69	[153]	Narcotics, woman-child repression, murder	Bangladesh (2012-2019)	Public	-	https://www.police.gov.bd/en/crimestatistic/year/2019
70	[154]	Undefined	Montgomery's police department (2016-2019)	Public	-	https://data.montgomerycountymd.gov/Public-Safety/Crime/icn6-v9z3/data
71	[155]	Arms act, robbery, dacoity, burglary, dacoity, speedy trial, murder, woman child repression, kidnapping, police assault, etc.	Bangladesh police (2010-2019)	Public	-	https://www.police.gov.bd/en/crimestatistic=year=2018;

TABLE 2. *(Continued.)* **Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).**

72	[156]	Larceny, theft, assault, drug, vandalism, vehicle theft	Chicago and San Francisco (2003-2017)	Public	-	https://data.sfgov.org/Public-Safety/Police-Department-Incident-Reports-Historical-2003/tmnf-yvry/about_data https://data.cityofchicago.org/stories/s/Crimes-2001-to-present-Dashboard/5cd6-ry5g
73	[157]	Assault, burglary, drug, fraud, robbery, vandalism, warrants, sex offences, kidnapping	San Francisco (June 2003-May 2015)	Public	-	https://datasf.org/opendata/.
74	[158]	Undefined	Boston dataset (2015-2018)	Public	Kaggle	https://www.kaggle.com/ankkur13/boston-crime-data
75	[34]	Drug, alcohol, firearms, felony, violence	ICPSR (Inter-University Consortium for Political and Social Research), 1994, prisoners in 15 states (Arizona, California, Delaware, Florida, Illinois, Maryland, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Texas, and Virginia)	Private	-	-
76	[159]	Murder, domestic violence, drug, rape, dowry, poison death, fraud, revenge	Indiastats, kaggle, and etc.(2013-2021)	Public	-	No Links
77	[160]	Undefined	LA (2020-2022)	Public	-	https://www.kaggle.com/datasets/hemil26/crime-in-los-angeles
78	[161]	Theft, battery, criminal damage and narcotics	Chicago Crime dataset (2020)	Public	Chicago Data Portal	https://data.cityofchicago.org/
79	[162]	Undefined	Boston dataset (from July 1, 2016 to August 1, 2017)	Public	-	No Links
80	[163]	Undefined	Vancouver city (2003-2021)	Public	-	https://vpd.ca/crime-statistics/
81	[164]	Burglary, Pickpocketing, Vehicle theft, Assault	Central China, (from January 1, 2016 to December 31, 2016)	Private	-	-
82	[17]	Theft (public places, pickpocketing, and robbery)	Public Security Bureau (2017-2019), ZG City/China	Private		-
83	[21]	Murder	The Murder Accountability Project (MAP) and FBI (1976–2019)	Public	-	https://www.murderdata.org/p/data-docs.html
84	[165]	Burglary, rape, robbery, and vehicle larceny	NYC (07/01/2012-06/30/2023)	Public	-	No Links
85	[166]	Auto theft and wallet theft, physical integrity, domestic violence or threats and coercion, drug	Public Safety Police of Porto (2016-2018)	Private	-	-
86	[167]	Burglary	Israel (2009–2017); NYC (2012–2014)	Public	-	http://data.cityofnewyork.us/Public-Safety/Police-Precincts/78dh-3ptz;
87	[168]	Burglary, theft, street crimes, violent crime	Atlanta, Austin, Detroit, Los Angeles, Philadelphia, San Francisco, Chicago, Portland (2017)	Public	-	https://opendata.atlantapd.org/; https://data.austintexas.gov/; https://data.detroitmi.gov/; https://data.lacity.org/; https://opendataphilly.org/; https://datasf.org/opendata/; https://datasf.org/opendata/; https://nij.ojp.gov/
88	[169]	Petit larceny, harassment, burglary, criminal mischief, grand larceny	New York City crime data (2010–2017)	Public	-	https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i/data
89	[170]	Undefined	Los Angeles (from July 1, 2015 to January 1, 2016)	Public	-	Not applicable.

TABLE 2. *(Continued.)* **Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).**

90	[171]	Theft	Chicago (from January 1, 2016, to December 31, 2017)	Public	-	https://data.cityofchicago.org/
91	[172]	Robbery (household, motorcycle, people)	National Police of Ecuador (2017)	Private	-	-
92	[32]	Drug crime	Drug rehabilitation centers and high school students	Private	-	-
93	[173]	Property and violent crimes	Baltimore, Minneapolis Austin, Chicago (from August to December 2020)	Public	Open data portals of the cities	No Links
94	[174]	NYC (burglary, robbery, assault, larceny), Chicago(burglary, robbery, assault, narcotics)	NYC and Chicago (from January 2014 to December 2015)	Public	-	No Links
95	[175]	Dacoit, theft, robbery, burglary, and other offenses	The National Crime Records Bureau of India (2001-2019)	Public	-	https://ncrb.gov.in/en
96	[176]	Criminal sex abuse by family member, Sex assault of child by family member, Aggravated sex assault of child family member, Child abuse, Child pornography	Chicago's open data portal (from January 2001 to December 2021)	Public	Chicago data portal	https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2/about_data
97	[177]	Theft, burglary, assault, robbery, vandalism	San Francisco Police Dep. (from January 2005 to April 2015)	Public		https://sanfranciscopolice.org/stay-safe/crime-data/crime-reports
98	[178]	Possession of weapons	Metropolitan police, UK (from January 2021 to December 2021)	Public	Github	https://www.met.police.uk/sd/stats-and-data/Waristkhanahmadzai/Weapon-offence-charges-and-Stop-Search-dataset
99	[179]	Theft, drug(Narcotic), criminal trespass	Chicago Police Department	Public	Kaggle	No Links
100	[180]	Rape, abduction and kidnapping, crimes against women, dowry deaths, assault on women	India (2017-2020)	Private	-	-
101	[181]	Burglary	Crimes in US Communities Dataset (2018)	Public	Kaggle	https://www.kaggle.com/datasets/michaelbryantds/crimedata
102	[182]	Theft (public places, pickpocketing, and robbery)	Public Security Bureau, ZG City/China (from January 1, 2014 to December 31, 2019).	Private	-	-
103	[183]	Murder, violence, hurt, rape	India (2001-2012)	Public	Kaggle	https://www.kaggle.com/datasets/rajanand/crime-in-india
104	[184]	Theft, assault, drug, vandalism, burglary, robbery, fraud, missing person, prostitution and gambling, sex offenses	San Francisco (from January 1, 2003 to May 13, 2015)	Public	-	https://data.sfgov.org/browse
105	[185]	Murder and non-negligent manslaughter, rape, robbery, and aggravated assault	Little Rock Police Department, Arkansas, USA (January 2017-November 2021) (from November 2021 to March 2023)	Public	-	https://data.littlerock.gov/
106	[186]	Shoplifting, pocket picking	Boston Police Department	Public	-	https://police.boston.gov/shopping-pocketbook-safety/
107	[187]	Murder, rape, theft	India (2001-2018)	Private	-	-
108	[188]	Willful murder, aggravated assault, rape, robbery, theft, abduction, grand auto theft, burglary, drugs, human trafficking	Dubai Police (2014-2018)	Public	-	https://www.dubaipolice.gov.ae/wps/portal/home/opendata/majorcrimestatistics/!ut/p/z0/04_Sj9CPykssy0xPLMnMz0vMAfIjo8zi_T29HQ2NvA18_V2NzQwCA_y9Ayy83Y3cvcz0g1Pz9AuyHRUBB3FbHA!!/

TABLE 2. *(Continued.)* **Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).**

109	[74]	Undefined	Chicago (2012-2017)	Public	Kaggle	https://www.kaggle.com/datasets/vic666/chicago-crimes-2012-to-2017
110	[189]	Theft, prevalent crime, battery, criminal damage, narcotics, assault, burglary, motor vehicle theft, fraud, robbery, others.	Chicago (2001-2023)	Public	Data.gov	https://catalog.data.gov/dataset/crimes-2001-to-present
111	[190]	Undefined	Denver Police Department (2010-2018) LA (2014-2016)	Public	-	No Links
112	[191]	Arrest	Five Boroughs of New York City	Public	NYPD	https://data.cityofnewyork.us/Public-Safety/NYPD-Arrests-Data-Historic-/8h9b-rp9u/about_data
113	[192]	Kidnapping, burglary, murder, rape,robbery, theft	India, Dataset of Kerala State (2014-2018)	Public	Kaggle	https://www.kaggle.com/datasets/ramjasmaurya/kerala-crime-records-2016-aug-2022
114	[193]	Robberies, homicide child abuse	Annual Reports of the Sri Lanka Police Statistics Division	Public	-	https://www.police.lk/?p=10492
115	[194]	Homicide, offenses against morality, other offenses against persons, robbery, breakings, theft of stock, stealing, theft by servant, vehicle and other thefts, dangerous drugs, criminal damage	Annual Crime Reports, Kenya National Police Service	Public	-	https://www.npsc.go.ke/annual-reports/
116	[195]	Rape, violence, kidnapping, sexual harassment	India (Madhya Pradesh Government Database)(2005-2012)	Public	-	https://www.india.gov.in/website-directory-madhya-pradesh-government
117	[196]	Violent, homicide, robbery, aggravated assault, burglary, vehicle theft, larceny	Baltimore City (from December 2010 to February 2023)	Public	-	https://data.baltimorecity.gov/datasets/baltimore::part-1-crime-data/about
118	[197]	Theft, vehicle theft, burglary,drug, robbery	LA (Jan 2015 to Dec 2015); Chicago(from January 2018 to December 2018)	Public	Chicago and LA crime datasets	No Links
119	[198]	Burglary, battery, aggressive theft, violent	A, B, C local police departments in Belgium (2012-2016)	Private	-	-
120	[199]	Crimes against women	India (2016-2021)	Public	-	No Links
121	[35]	Theft, criminal damage, battery, narcotics	Chicago (2019) and NYC (2019)	Public	Chicago, NYC	https://data.cityofchicago.org/Public-Safety/Crimes-2019/w98m-zvie/about_data https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i/about_data
122	[200]	Undefined	Chicago (2001-2021)	Public	Chicago data portal	https://data.cityofchicago.org/Public-Safety/Crimes-2014/qnmj-8ku6/about_data
123	[201]	Undefined	Chigaco (2015-2019)	Public	ICPSR	https://www.icpsr.umich.edu/web/ICPSR/studies/37256/versions/V1
124	[202]	Assault, larceny, burglary and robbery	NYC (from January 2014 to December 2014)	Public	-	https://opendata.cityofnewyork.us/

TABLE 2. *(Continued.)* Summary of the papers analyzed in the review. The table includes the reference to each paper, the type of crime, a description of the dataset(s) used, whether the dataset(s) is (are) public or private, the dataset(s) source, and, if available, the dataset link(s).

125	[203]	Dangerous weapons, burglary, robbery, larceny, harassment, assault, against public order, drug	NYC (2014-2015)	Public	NYC data portal	https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i/about_data
126	[204]	Violence	Survey private dataset	Public	Github	https://github.com/mjdominguez/LPIPV-
127	[205]	Homicide, thefts, shoplifting and robberies	Colombian National Police (2012-2017)	Public	-	https://www.policia.gov.co/grupo-informacion-criminalidad/estadisticadelictiva
128	[206]	General	Saudi Arabia (2018)	Public	-	https://github.com/sbahli/Crimes
129	[70]	Robbery	Dallas Open Data (2014-2018)	Public	Dallas	https://www.dallasopendata.com/
130	[207]	General	Denver (2016-2021)	Public	-	https://www.denvergov.org/opendata/dataset/city-and-county-of-denver-crime
131	[208]	Larceny, violence, drug, assault	Boston Police Department (2016-2017)	Public	Kaggle	https://www.kaggle.com/ankkur13/boston-crime-data/home
132	[209]	Undefined	NYC Crime and CHI Crime (Undefined)	Public	-	No Links
133	[71]	Larceny/theft, vehicle theft, drug, burglary, violence, assault	San Francisco (2003-2015)	Public	Kaggle	https://data.sfgov.org/Public-Safety/SFDATA/nkq3-jtjd/about_data
134	[210]	Murder attempt, rape, kidnapping, robbery, theft	India -Tamil Nadu (2001-2016)	Private	-	-
135	[211]	General (several criminal kinds)	London's criminal histories (2020-2021)	Public		https://data.london.gov.uk/dataset/mps-monthly-crime-dahboard-data
136	[212]	Violence, theft, rape, forced harassment, murder and robbery	Seoul Open Data (2004-2013)	Public		https://data.seoul.go.kr/
137	[213]	Violent, property, drug, and other crime	Chigaco (2014-2016)	Public		https://data.cityofchicago.org/stories/s/Crimes-2001-to-present-Dashboard/5cd6-ry5g
138	[73]	Theft, robbery, murder, dacoity, hurt, rape, attempted murder, rioting, kidnapping and abduction	NCRB's official website (2012-2020), India	Public		https://data.gov.in/ministrydepartment/national-crime-records-bureau-ncrb
139	[214]	Burglary, larceny, robbery, assault, theft, battery, damage	Chigaco (from January 2016 to December 2017): NY (from January 2014 to December 2015)	Public	-	No Links
140	[215]	Burglary, larceny, robbery, assault, theft, battery, damage	Chigaco (from January 2016 to December 2017): NY (from January 2014 to December 2015)	Public	-	No Links
141	[216]	All crime types	Chicago(2001-2020), New York (2006-2019),Lahore (2015-2016) crime datasets	Public	Kaggle	https://www.kaggle.com/datasets/umairbutt/crime-prediction-chicago-newyork-lahore/data
142	[217]	Theft, car theft, motorcycle theft, lorry/van/truck theft, snatch, and burglary.	Royal Malaysia Police (RMP)(2011-2020)	Private	-	-

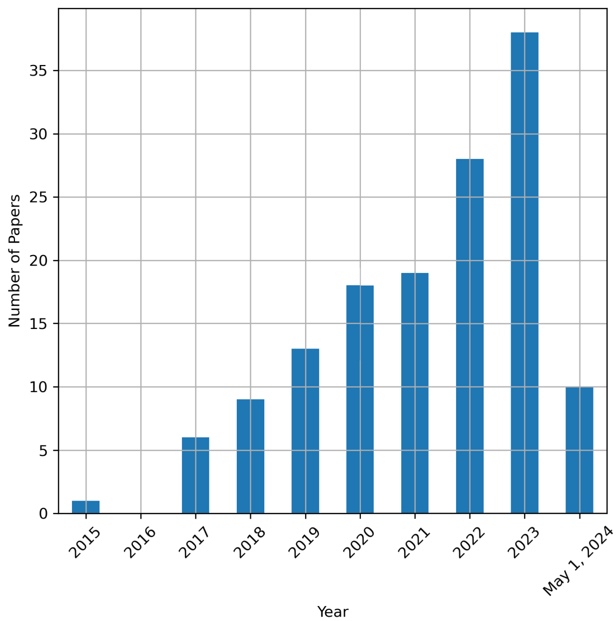

FIGURE 3. Distribution of publications using AI technologies per year from 2015 to May 1, 2024.

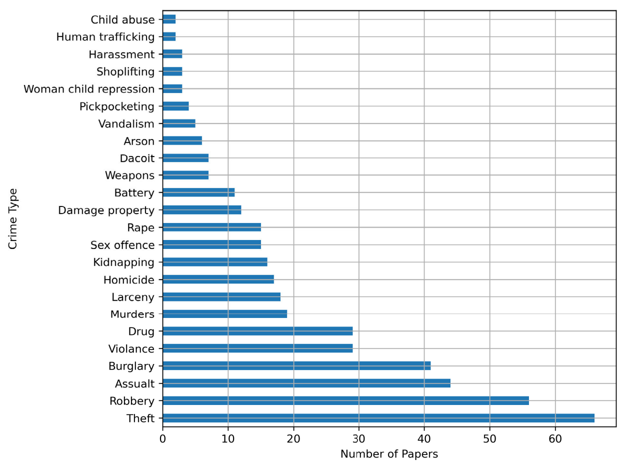

FIGURE 4. Distribution of papers based on crime types.

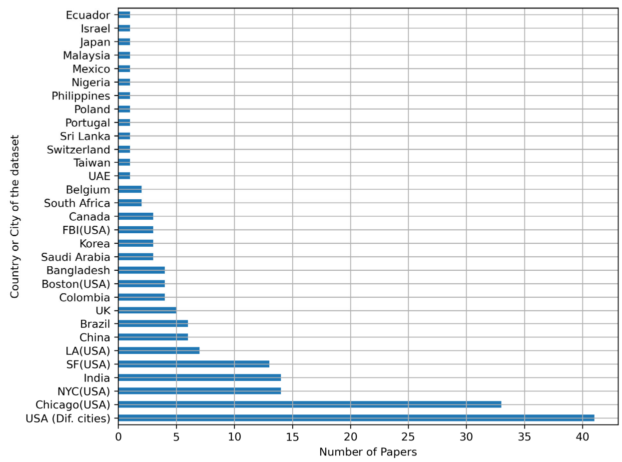

FIGURE 5. Distribution of papers based on countries and/or cities where the datasets were collected. The US Federal Bureau of Investigation (FBI) is also cited as a source of information.

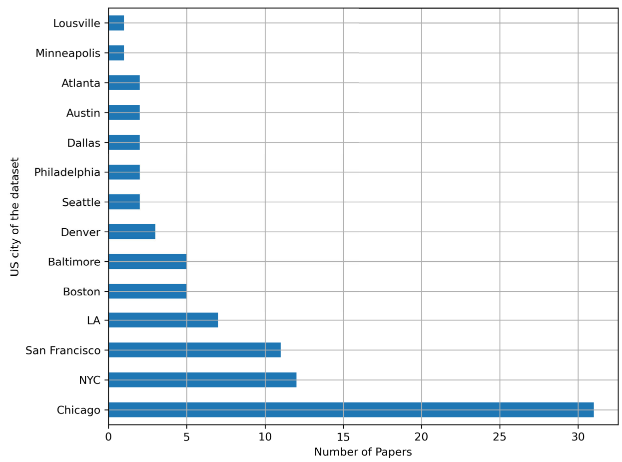

FIGURE 6. Distribution of papers based on US cities where the datasets were collected.

shows the distribution of papers which used datasets collected from USA cities. The Chicago dataset (33.70%) is the most extensively studied in crime prediction research. This is followed by datasets from New York City (NYC) (13.04%), San Francisco (11.96%), and Los Angeles (LA) (7.61%). Other frequently used datasets originate from Boston and Baltimore (5.43%), Denver (3.26%), and cities such as Seattle, Philadelphia, Dallas, Austin, and Atlanta (2.17% each). Meanwhile, datasets from Louisville and Minneapolis account for 1.09% each.

The third aspect takes into consideration whether the dataset is public or private. The availability of public crime data significantly enhances both the development of analytical processes and the effectiveness of ML and DL applications in crime analysis. These datasets enable researchers to gain deeper insights into criminal behavior and to design effective prevention strategies. Notably, police departments in cities such as Chicago, New York City (NYC) [35], [191], [203], and San Francisco [76], [130], [135], [186], [202], [209], [218] manage data portals that are widely utilized in crime prediction models. These portals provide publicly accessible datasets containing actual crime records collected by law enforcement agencies. Importantly, access to these datasets is not limited to police organizations; they are also available to researchers, journalists, and the general public. This transparency not only facilitates a better understanding of urban security policies and practices but also contributes to more informed public discourse.

Figure 7 shows the yearly distribution of papers utilizing public and private datasets. Specifically, 77.55% of the datasets utilized were public, while 22.44% were private. We observe that the use of public datasets has increased in all years, except for 2018. In 2023, almost 90% of the researchers used public datasets. Many public crime

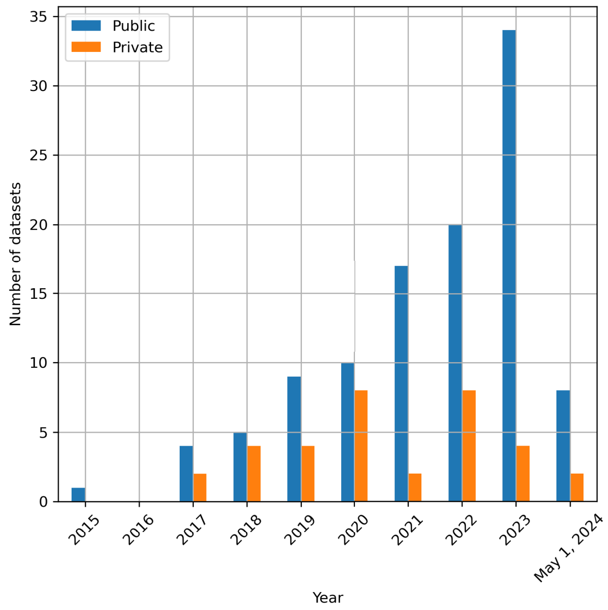

FIGURE 7. Yearly distribution of papers utilizing public and private datasets.

datasets are sourced from the NYC [35], [191], [203] and Chicago police departments [35], [106], [144], [161], [200]. Additionally, numerous public datasets can be found in databases such as UCI [92], [95], Kaggle [71], [122], [138], [147], [158], [179], [183], [192], [216], [219] and GitHub [178], [204]. These data portals not only offer a wide array of datasets but also include accompanying code and documentation. This comprehensive support contributes significantly to the learning and development of the data science community, facilitating more effective research and educational endeavors. Despite the reliance on these sources, the number of datasets available for crime investigations is very limited, with most lacking critical time and location information. This gap highlights the pressing need to make more of these datasets publicly accessible to enhance the effectiveness of crime research and predictive modeling [88], [89].

B. ANALYSIS OF THE APPROACH TYPES USED IN CRIME PREDICTION

The second part of this review outlines the various approaches employed in crime prediction research, including objectives, prediction techniques, best-performing methods, and model explainability. Figure 8 presents the distribution of crime prediction approach types used in the papers considered in this review.

The findings reveal that traditional ML techniques are the most commonly used in crime prediction studies, accounting for 42% of the approaches. These are followed by DL techniques, which constitute 26%; GIS-based hotspot prediction methods, which account for 20%; and statistical

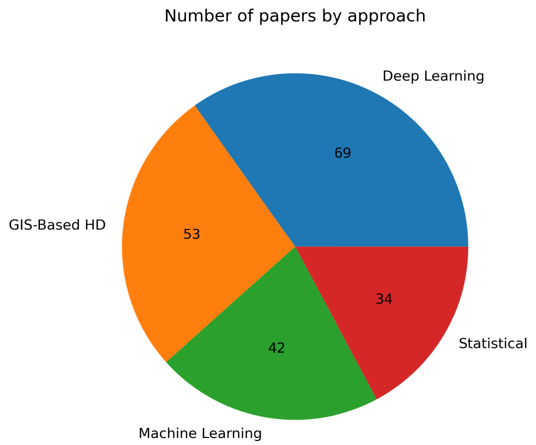

FIGURE 8. Distribution of approach types used in crime prediction research.

techniques, particularly time series methods, which make up 13% of the approaches.

Notably, hybrid approaches, which merge statistical methods, GIS-based hotspot techniques, and ML/DL models, have achieved significant advancements in crime prediction [73], [97]. These approaches are particularly effective in pre-crime predictions, as they analyze and correlate spatial and temporal crime patterns [61], [70], [135], [207]. Studies integrating these methodologies have demonstrated notable improvements in predictive efficiency and are increasingly applied to various facets of crime prediction [137], [140], [166], [169], [215].

1) ANALYSIS OF PREDICTION OBJECTIVES

Different objectives of crime prediction were addressed in various studies, with some papers encompassing multiple objectives, such as predicting crime occurrences (rate, count, etc.), predicting crime types, identifying spatio-temporal crime hotspots. The distribution of the papers based on these objectives is illustrated in Figure 9. The most frequently pursued objective is the prediction of spatio-temporal crime hotspots, representing 36.62% of the studies. This is followed by the prediction of crime types, which accounts for 31.69%, crime occurrences at 23.24%, and other objectives at 8.45%. The last category, 'other objectives', contains studies that could not be categorized separately due to their low frequency and diverse goals. This category includes studies on assessing racial fairness in prisons [34], comparing predictive policing methods [131], predicting suspect attributes [120], analyzing criminal behavior based on arrest history [110], forecasting cleared homicides at the national level [21], identifying the causes of adolescent drug addiction and predicting the likelihood of engaging in crime [32], predicting minor and major sexual victimization [106], evaluating the effectiveness of police 'stop and search' interventions [178], and estimating the probability of female victims of violence opting not to pursue legal action against their aggressors [204].

Research findings reveal that predicting spatio-temporal crime hotspots has become one of the most sought-after

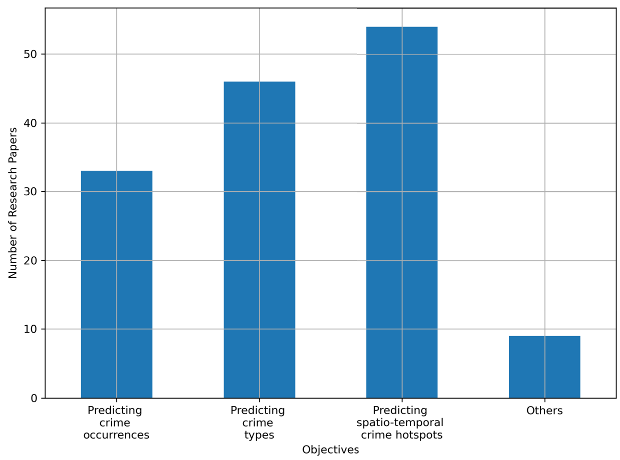

FIGURE 9. Distribution of the papers based on crime prediction objectives.

objectives in crime prediction studies. This approach is crucial as it integrates both temporal and spatial dimensions, providing a more comprehensive understanding of the dynamics of crime incidents [33], [120], [177], [203]. Since 2020, there has been a noticeable shift towards combining crime mapping with visualization support in crime prediction research [120], [148], [175]. This shift reflects the growing demand for user-friendly tools that enable analysts and decision-makers to interpret complex crime data intuitively. Crime mapping, powered by GIS, visually represents crime incidents across various locations. Additionally, the incorporation of advanced visualization techniques—such as heat maps, 3D visualizations, and dynamic time-series plots—has enhanced the analysis of spatio-temporal patterns. The integration of these tools with real-time data feeds holds immense potential for predictive policing. By leveraging these techniques, authorities can proactively address areas with higher crime risks based on patterns revealed through advanced mapping and visualization technologies.

2) ANALYSIS OF PREDICTION TECHNIQUES

A wide array of techniques has been applied in crime prediction research, with 20 techniques identified as widely used. Classical ML techniques dominate the field. Figure 10 shows the distribution of the papers based on the 20 widely employed techniques in crime prediction. RF is the most commonly used technique, appearing in 16.05% of studies (69 papers). This is followed by other ML techniques such as DT (11.15%) (48 papers), SVM (9.07%) (39 papers), NB (7.91%) (34 papers), KNN (7.91%) (34 papers), LogReg (6.51%) (28 papers), linear regression (4.88%) (21 paper), XGBoost (3.95%) (17 paper) and BBoost (2.56%) (11 paper). DL-based techniques ranked second. The most used DL technique is LTSM (4.42%)(19 papers). It is followed by MLP (3.72%) (16 papers), NN (3.26%) (14 papers) and CNN (3.26%) (14 papers). Among statistical time series techniques, the ARIMA model is used in 3.49% of the studies (15 papers), followed by SVR (3.02%) (13 papers). In addition to these commonly used techniques, new and emerging methods have shown high performance such as Gradient Boosting Trees (GBT), Spatio-Temporal Attention Units (STAU), Hybrid Recurrent Convolutional Framework (HRCF), Spatio-Temporal Attention-based Convolutional Learning for Crime (ST-ACLCrime), 3D ResNet-18, Local Search Genetic Programming (LSGP), and Conditional Generative Adversarial Networks (cGANs), among others. Additionally, the Hybrid Deep (HD) approach, which integrates ML and DL techniques, has been noted for significantly enhancing the visual representation and performance of crime prediction models [17], [73], [97], [147], [157], [143].

An important finding is that hybrid model approaches, which integrate multiple prediction techniques, are particularly effective. These hybrid techniques enhance model performance by leveraging the strengths of different models and algorithms, resulting in more accurate and reliable predictions. This observation aligns with findings from another review study, which also highlighted the benefits of using hybrid approaches in improving prediction outcomes [89].

One notable advancement, for instance, is represented by the development of a DL-based graph approach, namely the spatio-temporal deep fusion graph convolution network (STDGCN). STDGCN has been applied to datasets from Chicago and Los Angeles, combining statistical and DL techniques. This method has been found to outperform other techniques [197]. Additionally, another study introduces a probabilistic approach that divides crime into spatial areas, analyzing events within these areas through their interactions. This approach employs a spatio-temporal prediction model optimized using gradient-based techniques. The model's formulations are inspired by Hawkes processes [200], which are used to capture the temporal and spatial dynamics of crime events.

Another study involves a new prediction architecture that combines Graph Convolutional Networks (GCN) with multivariate Gaussian distributions applied to spatio-temporal data. This approach, implemented in the Graph-ConvGRU model, was compared with other DL, ML, and statistical techniques, and was found to outperform these methods [201].

Another innovative technique, named DeCXGBoost, integrates both ML and DL approaches. Applied to Boston crime data, DeCXGBoost outperformed all the various comparison ML and DL techniques [186].

In research focused on spatio-temporal criminal event location detection, the development of the AIST algorithm [35], a novel attention-based interpretable spatio-temporal network, has been a notable advancement. This algorithm aims to enhance the prediction of criminal offenses by leveraging attention mechanisms to provide interpretable and accurate predictions of crime locations over time. In addition to developing new prediction models, there is a broad range of research that delves into other critical aspects of crime prediction and analysis. These research focuses on integrating various data types, improving model interpretability, and

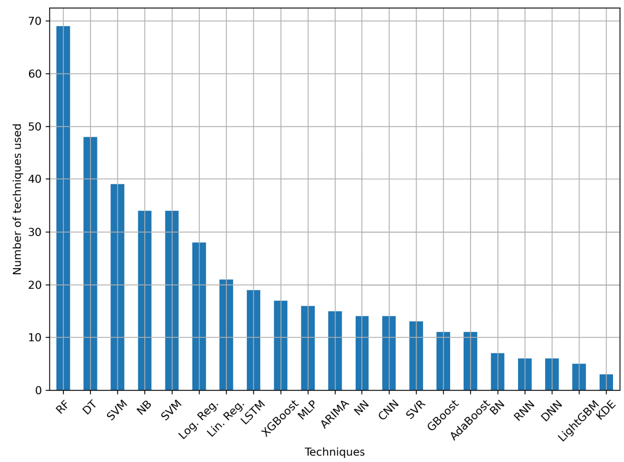

FIGURE 10. **Distribution of commonly used prediction techniques.**

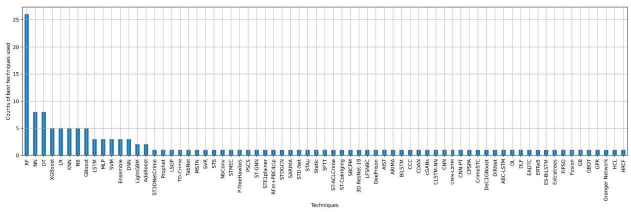

FIGURE 11. **Distribution of best prediction techniques.**

developing prediction strategies [156], [167], [170], [171], [174], [196], [220].

In the analysis of crime prediction studies, various techniques have been assessed for their performance. The performance distribution of different prediction techniques is visually represented in Figure 11. The technique with the best prediction performance is RF, which achieved 18.31% of the top-performing results. This indicates that RF is highly effective in predicting crime-related outcomes compared to other techniques. RF is followed by DT and NN techniques with 5.63%; LR, KNN, GBoost, XGBoost and NB with 3.52%; SVM, MLP, Ensemble models and DNN with 2.11%; LightGBM and LSTM with 1.41%. Additionally, other techniques were identified with 0.7%. Although some techniques from statistical time series (ARIMA, SARIMA) and ML techniques (AdaBoost, GBT) are seen among these techniques, most of them are DL techniques (cGANs, TabNet, STS, STMEC, STE1plainer, STDGCN, STD-Net, STAu, ST3DNetCrime, ST -GNN,ST-Cokriging, ST-ACLCrime, SFTT, SBCPM, Prophe, PSCS, P-TreeHawkes, NAHC, MSTN, LSGP, LFSNBC, H SLT (l,t), HRCF, HCL, Granger network, ES- BiLSTM, ERTwB, EADTC, E1tratrees, DeC1GBoost, DLF, DIRNet, CrimeSTC, CPSPA, CDAN, CCC, BiLSTM, AIST, ABC-LSTM, 3D ResNet-18).

3) ANALYSIS OF THE EXPLAINABILITY OF THE PREDICTION MODELS

In this section, we focus on explainability in crime prediction studies. Only a limited number of papers have addressed this aspect.

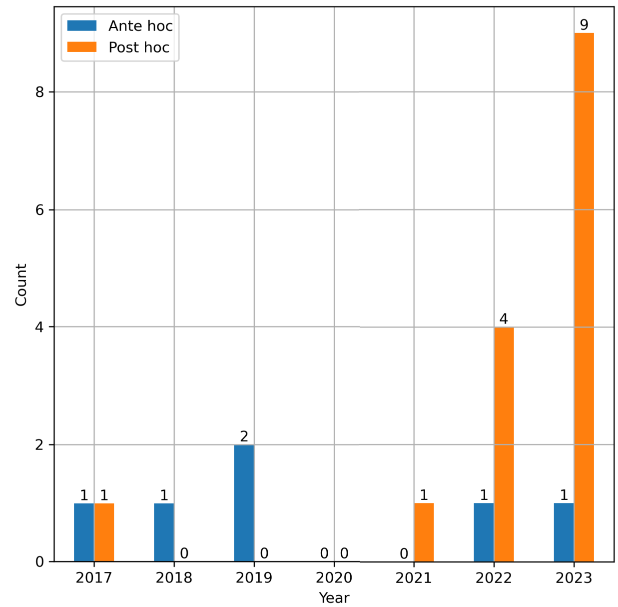

FIGURE 12. **Yearly distribution of papers where the best model explainability is discussed, addressed by ante-hoc or post-hoc strategy.**

Traditional ML techniques (e.g., LR, NB, DT, etc.) dominate crime prediction research, as they often require minimal post-hoc explanation [15], [94], [100], [106], [128], [143]. Other works involve the use of more complex models, providing insights with post-hoc explainability techniques into how predictions are made and enhancing trust in these models [17], [21], [32], [33], [78], [203], [207], [209].

The distribution of articles employing ante-hoc and post-hoc explainability in crime prediction is illustrated in Figure 12. The research findings reveal that post-hoc techniques have been increasingly utilized for explaining predictive models, particularly after 2021. Among post-hoc explainability studies, specific local crime research emerged as the most common focus, appearing in three papers. Additionally, post-hoc specific global, agnostic local, and global explainability were addressed in two papers each. In the domain of crime prediction, the Shap technique is the most frequently employed method for post-hoc explainability, as documented in several studies [17], [21], [32], [70], [76], [77], [181], [182]. The Lime technique follows in popularity, cited in [93] and [181]. These trends highlight a growing interest in post-hoc explainability techniques to better understand and interpret crime prediction models, particularly in the context of local and domain-specific crime patterns.

With the aim of providing a detailed overview of each article along the dimensions discussed in this Section VI-B, Table 3 summarizes key aspects of each paper, including the research objective, the types of crime prediction techniques used, the best-performing prediction model, the possible use of XAI models, and whether a discussion on explainability

TABLE 3. Summary of the papers analyzed in the review. The table includes the objectives, the types of crime prediction techniques used, the best-performing prediction model, the use of XAI models, and whether a discussion on explainability is provided. Regarding the objectives, we classify them as follows: (1) Predicting crime occurrences, (2) Predicting crime types, (3) Predicting spatio-temporal crime hotspots, and (4) Other objectives.

N.	Ref.	Obj.	Crime prediction approach type	Crime Prediction Models	Best Model	Explainable AI		Comments on expl.
						Ante-Hoc	Post-Hoc	
1	[92]	1	ML	Multivariate Adaptive Regression Splines (MARS), SVM, RF	RF			No
2	[93]	1	ML	SVM, LR, DT, RF	LR		Lime	Yes
3	[94]	1	HD, ML	Linear Regression	LR	■		Yes
4	[95]	1	ML, DL	GSGP, LSGP, isotonic regression (ISO), lin. Reg., Least squares regression (SQ), SVM, RBF, NN	LSGP			No
5	[96]	3	HD, Stat., ML, DL	DNN, SVM, KDE	DNN			No
6	[97]	3	HD, ML, DL	DL, NB, RF	DL			No
7	[98]	3	HD, Stat., ML	KDE, BayesNet, Naïve Bayes, J48, Decision Stump, Random Forest	RF			No
8	[99]	2	Stat., ML	OLS Regression, RF	RF			No
9	[100]	2	ML	BayesNet, DT, J48, Logistic, Naïve Bayes	DT	■		Yes
10	[101]	3	HD, ML	Log.Reg., SVM, RF, Ensemble	Ensemble (Log.R. + SVM + RF)			No
11	[12]	3	HD, ML	KNN, NB	KNN	■		No
12	[102]	2	ML	NB, DT, RF, NN, SVM	NN			No
13	[103]	3	HD, Stat., ML	ARIMA, KNN, AdaBoost	AdaBoost			No
14	[104]	1	DL	NN, LTSM, RNN, CNN	NN			No
15	[105]	3	HD, ML, DL	DNN, KNN, SVM, RF	DNN			No
16	[31]	2	ML, DL	3NN, DT, BN, J48, Log.R, MLP, NB, RF, SVM, RFm + PBC4cip	RFm + PBC4cip	■		Yes
17	[106]	4	ML	DT (Chaid)	DT	■		No
18	[107]	3	HD, ML	RF, MLP, KNN	MLP			No
19	[46]	3	HD, ML	RF, Log.Reg., AdaBoost	RF			No
20	[15]	2	ML, DL	MLP, SVM, DT, NN, Log.Reg., RF, CNN, RNN, LSTM, GRU	DT	■		Yes
21	[108]	3	HD, ML	RF, NB, Log.Reg., KNN, DT	RF			No
22	[109]	2	ML, DL	NB, RF, KNN, DT, DL	NB			No
23	[110]	4	ML, DL	SVM, DNN	SVM			No
24	[111]	3	HD, DL	LSTM	LSTM			No
25	[112]	3	HD, Stat.	Gaussian Process Regression (GPR)	GPR			No
26	[61]	2	HD, Stat, ML, DL	ARIMA, NB, SVM, KDE, DNN, LFSNBC	LFSNBC			Yes
27	[113]	3	HD, DL	NN	NN			No
28	[114]	3	ML	KNN, DT, NB, SVM	KNN	■		No
29	[115]	2	ML	NB	NB			No
30	[116]	2	ML	DT,RF, KNN, AdaBoost	RF			No
31	[117]	2	ML	KNN, SVM, RF, XGBoost	XGBoost			No
32	[118]	3	DL	CNN, LSTM, CLSTM-NN	CLSTM-NN			No
33	[119]	2	ML, DL	NB, RF, KNN, DT, DL	NB			No
34	[120]	3	HD, ML, DL	LSTM, KNN, RF, SVM, NB, CNN	LSTM			No
35	[121]	2	ML, DL	NB, Gradient boost, DNN, BN	Gradient boost			No
36	[122]	2	ML, DL	KNN, MLP, DT, Extratrees, ANN, SVM	Extratrees			No
37	[123]	3	HD, ML	Log.Reg., RF, SVM, DT	RF			No
38	[124]	3	HD, ML	NB, Log.Reg., RF	RF			No
39	[125]	3	ML	SVM	SVM			No
40	[126]	4	ML, DL	DNN, Log.Reg,, SVM, NB, XGBoost, KNN, GBDT, AdaBoost, LDA, QDA, RFC, DT), CNN, LTSM, Fusion model	Fusion model			No
41	[127]	1	Stat, DL	SMA, CNN-T, ARIMA, CNN, CNN-PT	CNN-PT			No
42	[128]	3	ML	RFR, ExtraTree, DT, Bagging	DT	■		No
43	[129]	1	ML, DL	GBoost, NN, Poisson regressor	GBoost			No
44	[130]	1	ML, DL	DeepCrime, RFR, Log.Reg., CrimeSTC	CrimeSTC			No
45	[131]	4	HD, ML	Near-repeat model, Ensemble model, Risk terrain model, Hotspot analysis	Ensemble model			Yes
46	[132]	1	DL	Spatio-Temporal Cokriging (ST-Cokriging)	ST-Cokriging			No
47	[133]	3	HD, ML	KNN	KNN	■		No
48	[134]	1	DL	NN	NN			No
49	[135]	3	HD, Stat, ML	SARIMA, Density based time series, RF, REPTree, ZeroR	SARIMA			No
50	[136]	2	ML	J48, RF, SMO, Begging, NB, ensemble-approach (SBCPM)	SBCPM			No
51	[137]	2	Stat, ML, DL	SVM, NB, KNN, MLP, XGBoost, LSTM, ARIMA, LogReg, DT	XGBoost			No
52	[138]	1	ML	LR	LR	■		No
53	[139]	2	ML	KNN, RF, AdaBoost, GBoost, Extra Trees	GBoost			No
54	[76]	2	ML, DL	SVM, LightGBM, RF, Stochastic Gradient Descent, KNN, AdaBoost, XGBoost , TabNet	TabNet		Shap	Yes
55	[140]	1	Stat., ML, DL	Mixed ST-Nets(MSTN), ST-Resnet, CNN, RNN, GBoost, LR, time series	MSTN			No
56	[141]	3	HD, ML, DL	DIRNet, SVM, RF, ST-ResNet, STCN	DIRNet			No
57	[142]	1	ML	RF, DT, SVR, MLP, Lasso Reg., Bayesian, Ridge Reg., LR	RF			No
58	[143]	3	ML	DT, Log.Reg., MLP	DT	■		No
59	[144]	2	DL	ST-ResNet, DMVST-Net, STD-Net	STD-Net			No
60	[145]	2	DL	3D CNN, 3D ResNet-18	3D ResNet-18			No
61	[146]	4	ML	RF, ERT, ERTwB	ERTwB			No
62	[147]	3	HD, ML, DL	CCRBoost, ST-ResNet, DT, NB, LogitBoost, RF, SVM, KNN, MLP, SFTT, TFTS	SFTT			No
63	[148]	3	HD, Stat, ML	RTM, Kernel density, RF	RF			Yes

TABLE 3. *(Continued.)* **Summary of the papers analyzed in the review. The table includes the objectives, the types of crime prediction techniques used, the best-performing prediction model, the use of XAI models, and whether a discussion on explainability is provided. Regarding the objectives, we classify them as follows: (1) Predicting crime occurrences, (2) Predicting crime types, (3) Predicting spatio-temporal crime hotspots, and (4) Other objectives.**

64	[77]	3	DL	cGANs	cGANs		Shap	Yes
65	[149]	3	HD, ML, DL	NN, LR	LR	■		No
66	[150]	2	ML	SVM, DT, RF, NB, Log.Reg.,	RF			No
67	[151]	3	HD, ML, DL	Kernel Warping (KW), Gaussian (GLoG), Static Count model	Static Count model			No
68	[152]	3	HD, Stat., ML	Simple linear regression (SLR), MLR, DTR, SVR, RFR	RFR			No
69	[153]	2	ML, DL	DT, KNN, MLP	DT	■		No
70	[154]	3	HD,ML	CNN, SVM	SVM			No
71	[155]	1	Stat., ML	LR, SVR, NN	NN			No
72	[156]	1	Stat.,DL	Bi-LSTM, ATTN-LSTM, FBProphet, SARIMAX, timedistrubuted dense, FLF, DLF	DLF			No
73	[157]	3	HD, ML, DL	NB, BN, KNN, MLP, Gausian NB, DT, RF, Adaboost, GBoost, LDA, QDA	GBoost			No
74	[158]	2	ML	DT, NB, Log.Reg.	DT	■		No
75	[34]	4	Stat., ML	EADTC (Evolutionary Algorithm Decision Tree), LR, Ridge regr. CART, RF, GBDT	EADTC	■		Yes
76	[159]	1	Stat., ML	SVR, Lasso Reg., RF, GBoost, ExtraTrees, Bayesian, Ridge Reg., ElasticNet	SVR			No
77	[160]	3	HD, Stat., ML	LR, LinearSVR, DT	DT	■		No
78	[161]	2	ML	NB, DT, RF	RF			No
79	[162]	1	Stat, ML, DL	DT, Extra Tree, KNN, AdaBoost, RF, Light GBoost, GBoost, LSTM,RNN, CNN, ARIMA, SARIMA	CNN			No
80	[163]	3	HD, ML	KNN, XGBoost, RF	XGBoost			No
81	[164]	1	Stat., ML DL	LR, SVR,RFR, GRU, DeepCrime, Mist,TRMF, BTTF, GDF-TD, TD-Crime	TD-Crime			No
82	[17]	3	HD, ML	RF, DT, XGBoost, LogReg	XGBoost		Shap	Yes
83	[21]	4	ML	Ridge Reg., LASSO, Elastic net, SVM, GBM, XGBoost, LDA, RF, DT	XGBoost		Shap	Yes
84	[165]	3	HD, Statistical, DL	ARIMA, VAR, LSTM, DMove, DST, STRN, CCRF, NCCRF, TCP, DCrime, CCC (Cross-type and spatio- temporal Correlations for Crime)	CCC			No
85	[166]	3	HD, Stat, ML, DL	NLP, Lasso Regression, Log.Reg., DT, RF, SVM	RF			No
86	[167]	3	HD, DL, ML	DeePrison, SVR,ARIMA, Log.Reg., TriMine, MLP, Wide&Deep, GRU, DeepCrime	DeePrison			No
87	[168]	3	HD, Stat.,	Granger network	GN			No
88	[169]	1	Stat.,ML, DL	ES-BiLSTM, RF, ARIMA, SARIMA, ZeroR	ES-BiLSTM			No
89	[170]	1	DL, ML	ST3DNetCrime, SVR, LSTM, ConvLSTM, ST-ResNet, ST-3DNet, ST-3DNet-s	ST3DNet Crime			No
90	[171]	3	HD, DL	HA, CNN, LSTM, CNN-LSTM, ConvLSTM, ST-ACLCrime	ST-ACLCrime			No
91	[172]	3	HD, Stat, ML	CPSPA (hybrid)	CPSPA			No
92	[32]	4	ML, DL	Log.Reg. KNN, SVM, RF, XGBoost, MLP	MLP		Shap, Lime	Yes
93	[173]	3	HD, DL	HALR, GRU, Attn, GGConv, GCN, NbConv	NbConv			No
94	[174]	1	ML, DL	SVR, GRU, MLP, GMAN, ST-SHN, MAPSED, STS	STS			No
95	[175]	2	HD, ML	NB, DT, RF	RF			No
96	[176]	2	HD, ML	DT, KNN, Gaussian NB, Log.Reg. AdaBoost, RF, ExtraTrees, XGBoost, Borderline SMOTE	RF			No
97	[177]	2	ML	KNN, SVM, DT, RF, NB, Log.reg., Ensemble method (KNN + SVM + DT)	Ensemble method			No
98	[178]	4	ML	RF, DT, NB	RF			No
99	[179]	3	ML	SVM, RF	SVM			No
100	[180]	2	ML	NB,SVM, LR,DT, Bagging Regression, Stacking Regression, RF	NB	■		No
101	[181]	3	HD, ML	Regression (Linear, Lasso, Ridge)	LR	■	Shap, Lime	Yes
102	[182]	3	HD, Stat., ML	Poisson Reg., KNN, DT, Bootstrap Aggregating (Bagging), RF, GBDT, XGBoost	GBDT		Shap	Yes
103	[183]	1	ML	NB, RF, SVM, DT, Log.R	NB	■		No
104	[184]	3	HD, ML	KNN, AdaBoost, RF,XGBoost, SGD,LightGBM	LightGBM			No
105	[185]	1	HD, DL	Prophet, NeuralProphet	Prophet			No
106	[186]	1	ML, DL	DeCXGBoost, NB,STK,RF, IBK, BAG, SVM, CNN, LWL	DeCXGBoost			No
107	[187]	2	ML	RF, SVM, DT, MLP, XGBoost	RF			No
108	[188]	2	ML, DL	RF, KNN, SVM, NN, NB, DT	KNN	■		No
109	[74]	2	ML, DL	ST-GNN,DT, Log.Reg., STMEC	ST-GNN		visual explanations	Yes
110	[189]	2	ML	NB, Log.R., KNN, DT, RF, NIL, Neural Integrated Random Forest, NINB, NILR, NIDT, NIKNN	Neural Integrated Random Forest			No
111	[190]	1	Stat.,ML,DL	CNN – LSTM, ARIMA, MLP, Random Fores, XGBoost, LogReg, KNN SVM	CNN-LTSM:			No
112	[191]	2	ML	DT, MLP, KNN, GBoosting	MLP			No
113	[192]	2	ML	RF, DT, GBoost	RF			No
114	[193]	1	Stat.	ARIMA	ARIMA			No
115	[194]	2	ML	DT, RF, Ada Boosted hybrid(RF+DT)	Ada Boosted hybrid			No
116	[195]	2	ML, DL	Log.Reg., RF, RF with SMOTE, ANN	ANN			No
117	[196]	3	HD, DL	STARIMA, ConvLSTM, ABC-LSTM	ABC-LSTM		visual explanations	Yes

TABLE 3. *(Continued.)* Summary of the papers analyzed in the review. The table includes the objectives, the types of crime prediction techniques used, the best-performing prediction model, the use of XAI models, and whether a discussion on explainability is provided. Regarding the objectives, we classify them as follows: (1) Predicting crime occurrences, (2) Predicting crime types, (3) Predicting spatio-temporal crime hotspots, and (4) Other objectives.

118	[197]	2	Stat., DL	STDGCN, ARIMA,SVR, Log.Reg, LSTM, MiST, GRU, CF	STDGCN			No
119	[198]	2	DL	NN	NN			No
120	[199]	1	ML	LR	LR	■		No
121	[35]	1	Stat., DL	AIST, ARIMA, DTR, Att-RNN, GBDT, Deep-Crime, Mist, GeoMAN, STGCN, MVGCN	AIST		Feature importance	Yes
122	[200]	1	DL	P-TreeHawkes, S-TreeHawkes, CNN-LSTM, CNN, RMTPP, RSTP	P-TreeHawkes			No
123	[201]	3	HD, Stat., ML, DL	HRCF, ARIMA, SVR, RF, GPR, ConvLSTM	HRCF			No
124	[202]	3	HD, Stat., DL	ARIMA, SVR, RNN, LTSM, GRU, Deep crime, stGCN, GMAN, CDAN	Cross Domain Attention Network (CDAN)			No
125	[203]	2	DL	MLP, GCN, TGCN, LSTM-GCN, STGCN, MiST, HAGEN, GSNet, STMEC	STMEC		Feature importance	Yes
126	[204]	4	ML, DL	NN, SVM, RF	NN		Anchors [245]	Yes
127	[205]	3	HD, ML	NB, KNN, SVM, RF	RF			No
128	[206]	2	ML	DT, RF, XGBoost, LGBM	RF			No
129	[70]	3	HD, ML	XGBoost, KNN, LR, RF	RF and XGBoost		Shap	Yes
130	[207]	3	HD, ML	Log.Reg., BN, KNN, DT, RF	RF			No
131	[208]	3	HD, ML	RF, DT, PCA-DT, PCA-RF	PCA-RF			No
132	[209]	1	ML, DL	HA, SVM, ST-ResNet, DCRNN, STGCN,STtrans, DeepCrime, STDN,ST-MetaNet, GMAN,ST-SHN, DMSTGCN, STExplainer-CGIB, STExplainer	ST Explainer		Feature importance	Yes
133	[71]	2	ML	LightGBM, RF, Log.Reg.	LightGBM			Yes
134	[210]	2	ML	KNN, NB, LR	KNN			No
135	[211]	2	Stat., DL	ARIMA, LSTM	LSTM			No
136	[212]	2	ML	RF, GBoost	GBoost			No
137	[213]	2	DL, ML	DNN, XGBoost	DNN			No
138	[73]	3	HD, ML, DL	PSCS, EfficientNet-B7, ResNet-152, VGG, CNN, LR, SVR, DTR, RFR	PSCS			No
139	[214]	2	DL	DeepCrime, ST-SH, ST-DP, STAu	STAu			No
140	[215]	1	Stat, ML, DL	SVM, ARIMA, ST-ResNet, DCRNN, STGCN, DeepCrime, GWN, STDN, ST-MetaNet, STtrans, GMAN, AGCRN, MTGNN, ST-SHN, DMSTGCN, ST-HSL, HCL	HCL			No
141	[216]	1	Stat., DL	SMA, WMA, EMA, LTSM, BiLSTMs, (CNN-LSTM	BiLSTM			No
142	[217]	1	ML	GLM, DT, RF, Gradient Boosted Trees(GBT), SVM	GBT			No

is provided. Notably, very few papers consider explainability aspects. In fact, several studies employ interpretable-by-design models, inherently implementing ante-hoc explainability. However, this is done unknowingly, as these models are commonly used in crime prediction. This is evidenced by the fact that no actual discussion on explainability is provided in the papers. Given the importance of making AI models transparent to enhance trust, as emphasized in this survey, this highlights a significant gap that needs to be addressed in future research on crime prediction.

VII. CONCLUSION AND FUTURE WORKS

Despite its potential, AI in crime prediction faces critical challenges, including issues related to fairness, accountability, explainability, interpretability, security, and privacy. Addressing these challenges is vital for developing AI models that are not only technically proficient but also ethically sound and socially responsible. The growing integration of AI technologies into crime prediction underscores the importance of creating systems that balance performance with trustworthiness, ensuring they contribute positively to public safety while minimizing the risks of misuse or harm.

This review makes a significant contribution by assessing the prediction models used in crime prediction, highlighting their strengths and the importance of improving their trustworthiness. In criminal investigations, the ability to understand and justify the results of predictive models is essential. Explainability plays a central role in building trust in AI systems and ensuring that decisions derived from these models are both transparent and defensible. This fosters accountability within law enforcement and enhances public confidence in the ethical use of AI.

Additionally, this research provides valuable insights into the datasets and techniques used in crime prediction. By exploring these aspects, it underscores the importance of making data sources accessible for improving prediction accuracy and enabling the broader adoption of advanced AI methods. Moreover, it highlights the critical role of ensuring data quality and integrity while safeguarding privacy and security in crime prediction systems.

Future research in crime prediction must address key challenges to enhance the effectiveness, reliability, and ethical integrity of AI systems. Developing advanced machine learning algorithms that manage diverse crime data while mitigating biases is crucial, alongside improving data collection by creating high-quality, diverse, and ethically shared datasets. Enhancing explainability through advanced XAI techniques and user-friendly tools will make AI systems more transparent and practical for law enforcement. Integrating emerging technologies like graph neural networks and federated learning can further improve performance and collaboration while preserving privacy. Ethical concerns such as fairness, accountability, and societal impact must remain central, with research focusing on evaluating and mitigating risks to ensure AI systems contribute responsibly to public safety. Bridging the gap between research and practice through accessible tools and training programs will also be essential. Finally, interdisciplinary collaboration and standardized benchmarks will drive innovation and ensure that AI tools are both effective and socially responsible. Addressing these priorities will transform AI into a powerful and ethical resource for crime prediction, fostering safer and more equitable communities.

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