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SURVEY ARTICLE

# AI-driven crime prediction: a systematic literature review

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## Abstract
The topic of crime analysis and prediction is crucial for public safety, and advanced AI has shown promise in enhancing this research area. Exploring these advanced AI-based schemes and summarizing them in one place can help communities such as policymakers, law enforcement agencies, and researchers. In this direction, literature presents some comprehensive state-of-the-art studies, however, these studies lack a thorough review of the latest AI methods used in crime prediction. This systematic literature review aims to fill these gaps by exploring recent advancements in Machine Learning, especially in Deep Learning, for crime prediction. This study delves into various digital repositories to extract relevant research articles using a robust qualitative selection process. A total of 55 top-quality research articles have been analyzed in terms of publishing venue, employed predictive model, geographical area for experiments, use of real-time data, data source, and time spans for crime records. The detailed analysis reveals that IEEE Access is a top publishing venue for crime prediction-related articles. In the dimension of applied techniques, traditional methods persist (33%), while innovative hybrid models and emerging techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Generative Adversarial Networks (GANs), Graph Neural Networks (GNNs) show a trend toward diverse integration. The geographical focus primarily centers on U.S. cities, appearing in 56% of the papers, highlighting global disparities. Additionally, there is a significant gap in incorporating real-time data in crime prediction models, underscoring the need for future exploration in this direction. These findings provide valuable insights for researchers, policymakers, and law enforcement agencies.

**Keywords** Crime prediction · AI · Machine learning · Systematic literature review · Deep learning

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## 1 Introduction

Crimes of a serious nature such as theft, vandalism, sexual assault, terrorist attacks, child labor abuse and murders, present a significant threat to public safety and societal progress. Worldwide, the Governments are continually exploring various methods to prevent the crimes. These methods include detecting unusual behavior in crowds [1], identifying instances of hate speech [2], and analyzing past crime incidents [3–7] to predict the future crimes. Among these methods, crime event analysis and prediction has gained popularity and proven effective over the past few decades. The traditional crime event analysis methods employed different methods in crime assessments [8–11], where statistical analysis is employed to evaluate the density, location, consistency, and importance of historical crime incidents. Predicting future crimes based on these patterns is important for taking preventive measures, enhancing security, and reducing the emergency response time.

However, more recently, Machine Learning (ML), particularly Deep Learning (DL), has shown promise in performing detailed and accurate crime analysis and prediction tasks [12]. In the past few years, the research community has presented effective state-of-the-art schemes for crime analysis and prediction in different regions of the world using advanced AI based predictive models [13–19].

Studying insights of these modern schemes and summarizing them at one place can help the researchers and other stakeholders to understand the advanced models used and areas covered for experimentation. Furthermore, the ignored dimensions or areas can be highlighted for future research. Motivated by the need for a comprehensive understanding of crime analysis and prediction schemes, this research aims to explore the advanced AI based techniques to predict criminal activities. As, by leveraging the power of advanced Deep Learning models, we seek to uncover hidden patterns, correlations, and trends that may outclass the traditional Machine Learning methods for crime prediction.

In pursuance of the targeted research direction, this study aimed to uncover the latest AI based techniques that had been proposed for crime prediction in different parts of the world. As, unveiling these advanced AI based techniques and summarizing at one place can help the policy maker, law enforcement agencies, and researchers who are working on crime prediction strategies. In the first step, to evaluate the previous work we extracted the previous review studies through a structured query string. From the appearing review papers, only the very recent and qualitative studies were selected to find the gap. These studies like [12, 20–23], provide significant insights from the literature related to crime prediction schemes, however these studies have presented some limitations that need to be addressed as listed below.

- Adoption of Latest AI Techniques:

  Many past reviews only covered studies until 2021, leaving a significant gap in keeping up with the fast developments in AI and Machine Learning techniques. They missed incorporating the latest AI methods for predicting crimes.

- Selection Process Concerns:
  There is a recurring issue in how research papers are chosen for reviews. Most reviews lack a clear system for selecting papers, which could introduce bias and cause them to miss important relevant work.
- Overlooking Important Repositories:
  Many research papers missed searching through important repositories for the latest advancements in crime prediction. This oversight can limit the exploration of the relevant work in the field.
- Geographical Variation Oversight:
  Existing studies often did not consider the frequency of primary research with respect to geographical areas chosen for experiments. Crime patterns can vary significantly between regions and countries, and this aspect needs more attention.
- Lack of Focus on Real-time and Historical Data:
  The studies did not emphasize the importance of analyzing research in terms of real-time and historical data.
- Neglect of Dataset Timespan:
  The existing review papers did not pay attention to analyzing the primary research with respect to time-span of the datasets used. Some studies only considered a few months, while others extended over decades. This variation needs to be acknowledged in the literature.
- Non-quantification of Data Source:
  Most of the existing review papers did not quantify research articles concerning the data source. It is important to know if the data comes from social media, dataset repositories, news articles, police reports, other government institutions or newspapers.

This study aimed to fill this gap by delving into the insights of recent research that has employed modern Machine Learning and Deep Learning techniques for crime predictions.

### 1.1 Dimensions of the gap

This research provides a countable contribution in the following dimensions of the gap we find in existing literature.

- Targeted digital repositories
- Survey approach
- Latest reference
- Quality assessment of literature
- Scheme for selection of paper
- Type of crimes
- Geographical area for experiment
- Data source
- Evaluation metrics

### 1.2 The gap matrix

This systematic review aimed to comprehensively explore the digital repositories focusing on crime prediction related studies. Our analysis spans multiple dimensions, including the targeted repositories, survey approaches employed, the recentness of studies considered, and the quality assessment criteria applied. The gap matrix presented in Table 1 serves as a structured framework to identify and analyze gaps in the literature concerning reviews of crime prediction studies, their geographical contexts, and the evaluation metrics used. By systematically analyzing these dimensions, we aim to contribute to identifying future research directions and enhanced understanding of the complexities surrounding crime prediction related studies.

After a critical review of the existing literature, the research gap is identified and summarized in Table 1. A systematic approach is employed to search for and select only high-quality research articles in the domain. Furthermore, the selected corpus is analyzed across multiple dimensions. This comprehensive study aims to help researchers understand modern crime prediction techniques discussed in the literature and adapt these methods for application in various parts of the world. Additionally, recent and advanced methodologies in crime prediction are explored to support stakeholders working in this field.

Following the introduction, the paper delves into existing research on AI-driven crime prediction (Sect. 2), outlining the methodology for a systematic literature review in Sect. 3. This includes details on research objectives, search queries, and selection criteria. Section 4 presents the results, including data collection, taxonomy development, and an analysis of included and excluded studies. It then dissects the findings in relation to each research question with supporting metrics. Finally, Sect. 5 offers discussions and some identified limitation in literature.

## 2 Literature review

This section discussed the prominent existing work that covered the analysis of studies relating to crime analysis and predictions using advanced AI techniques. The state-of-the-art studies have been analyzed in different dimensions. This critically analyzing process identified some limitations in the existing literature.

In a comprehensive study, [20] investigated the application of AI techniques for crime prediction, focusing on four central research questions. They find that crimes and spatial analysis are predominant areas of interest, with "crime density" being the most commonly used approach in recent years. The most frequently studied crime types are robbery, murder, and burglary as per the literature survey. Their detailed review also highlights that supervised learning is the dominant ML approach in this crime prediction field. This study mentioned that “random forest" and "naïve bayes" is the most utilized algorithms for crime prediction. This study found that among the 43 different performance metrics, "mean error," "accuracy," and the "true positive rate" are commonly employed in literature. According to this study, 40 different datasets, with Chicago, India, and the

Table 1 The gap matrix

| References | Targeted digital repositories | Survey approach | Latest ref. | Quality assessment | Scheme for selection of Paper | Type of crimes | Geographical area for experiment | Data source | Evaluation metrics |
|---|---|---|---|---|---|---|---|---|---|
| [20] | 5 | Systematic Search | 2021 | ✓ | ✓ | ✓ | × | × | ✓ |
| [23] | N/A | Informal | 2021 | × | × | × | × | × | ✓ |
| [12] | 3 | Systematic Search | 2022 | × | × | × | ✓ | ✓ | ✓ |
| [22] | N/A | Informal | 2021 | × | × | ✓ | ✓ | ✓ | ✓ |
| [21] | N/A | Informal | 2020 | × | × | ✓ | × | × | × |
| This Paper | 11 | Systematic, Snowballing | 2023 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

US being the most prevalent sources is being used in literature from crime predictions. The review identifies tools commonly used in crime prediction, including Weka, Python, and R. Strengths and limitations of ML approaches are discussed, along with possible future directions. The authors conclude that AI technologies show efficient results in enhancing crime prediction and prevention, particularly through the use of hybrid models, and suggest further research into technical aspects of crime prediction.

In another study, [23] focused that crime prediction rely on analyzing historical data with the help of Deep Learning, statistical models, and algorithms. It examines various global approaches to predicting and forecasting crime occurrences, categorizing them into following three groups:

(a) Neural network-based approaches
(b) Statistical approaches
(c) Spatiotemporal approaches.

The effectiveness of these methods is assessed in terms of precision and accuracy to present existing methodologies and report the need for future advancements. This study reviewed eight selected papers to identify gaps in existing approaches and provides a comprehensive understanding of the different methods used in the field, offering valuable insights into the evolving landscape of predictive policing and crime prediction. They mentioned that, predictive policing, which complements traditional policing, relies on empirical data and advanced statistical models to predict areas of higher criminal activity, potentially leading to crime reduction. The paper mentioned the challenges in collecting and analyzing crime data and underscores the role of Artificial Intelligence and Deep Learning in processing and predicting crime occurrences based on thousands of crime reports.

Recently, in a research, [3, 12] presented a thorough investigation into the application of Machine Learning (ML) and Deep Learning (DL) algorithms for crime prediction. By reviewing over 150 articles and conducting an in-depth analysis of 51 selected studies, the paper explored the potential of ML and DL techniques to enhance the accuracy and effectiveness of crime prediction models. It described the processes of crime prediction from data collection and preprocessing to feature engineering and model development. This study briefly discussed the datasets used in crime prediction studies, including those from major cities. The paper categorized the studies into ML-based regression and classification methods, offering examples of how these techniques are applied to predict different types of crimes in various urban settings. Furthermore, the research covers the use of Deep Learning algorithms, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), for both regression and classification tasks. It emphasizes the versatility of Deep Learning in handling different data types, including text, images, audio, and social media, for crime detection.

In 2022, [22] explored the use of data science and Machine Learning in predicting crimes, given the abundance of electronically recorded crime data. It categorized and reviewed recent studies in this field based on factors like demographics, spatial and temporal aspects, and the types of Machine Learning methods used. In literature, the studies cover a range of techniques, from basic ones like K-nearest neighbors and logistic regression for predicting crime trends to more advanced approaches using dynamic variables from social media data. Overall, this study highlighted the importance of Machine Learning in improving crime analysis and helping the criminal justice system.

In a literature review presented by [21], a collection of research papers has been reviewed, various studies tackle the task of predicting different types of crimes using Machine Learning and statistical methods. These studies span several years, locations, and crime datasets. Researchers have explored techniques like clustering, regression, and ensemble learning to make predictions about crimes, such as burglary and violence. For example, they use data-driven approaches, kernel density estimation, and rule extraction to enhance crime prediction. Some studies focus on reducing crime rates in specific areas, while others aim to identify crime hotspots in urban settings. These papers offer valuable insights into using technology to make communities safer by forecasting and preventing crimes. However, the study did not mention the recent Deep Learning-based methods for crime predictions.

### 2.1 The identified gap

The research gap found in the existing review papers is presented in Table 2.

### 2.2 Summary of gap within existing surveys

The research papers we looked at have some common problems. First, most of them don't keep up with the latest AI and Machine Learning advances, so they miss out on new techniques developed after 2021. Second, there's an issue with how they choose which papers to study, which could make their findings biased and cause them to miss important work. Also, many of these papers focus on old data and fixed time periods instead of using current information to predict crime. They also don't compare how well their predictive models work in different types of places, like cities and rural areas, where crime patterns can vary.

In summary, these research papers collectively need to address the challenges of staying current with the fast-paced advancements in AI, develop systematic criteria for paper selection, explore real-time crime prediction, compare different settings, and consider regional variations in crime prediction models. Additionally, they should explicitly mention and incorporate the latest Deep Learning techniques and be more comprehensive in reviewing relevant research studies to ensure a well-rounded literature review.

### 2.3 Novelty of this paper

Our goal is to learn more about this research area by carefully looking at all the dimensions that have not been studied yet. This study aims to provide a thorough

**Table 2** Identified gap in existing review papers

| References | Title | Year published | Gaps |
|---|---|---|---|
| [20] | Artificial intelligence & crime prediction: A systematic literature review | 2022 | (a) The paper does not discuss latest Deep Learning approaches as this study, mainly focused on traditional Machine Learning techniques<br>(b) The research paper mentioned a variety of crime types, but it did not cover the studies of all possible crime categoriese–g<br>Women abuse in homes<br>Child labor exploitations<br>Political corruption<br>Environmental corruption: (violations of environmental laws and regulations)<br>(c) The latest studies mentioned in this research is of 2021, whereas the latest technology evolvement in Machine Learning demands review of recent studies of crime prediction field |
| [23] | A survey on crime analysis and prediction | 2022 | (a) The quality is compromised due to its lack of a systematic approach in selecting research papers. As, without a predefined and rigorous methodology, the selection process is prone to bias and subjectivity, and could not be reproduce and can exclude significant studies. This oversight results in a review that may not comprehensively cover the relevant literature, thereby reducing the reliability and validity of its findings<br>(b) The reviewed papers are insufficient as in literature survey analyzing only 8 research papers can ignore a lot of quality work of the same time period<br>(c)The paper primarily focuses on techniques using historical data and fixed time periods. A research gap exists in the exploration of real-time crime prediction schemes, where data from ongoing events and real-time information sources is used in predictive models<br>(d)A research gap exists in comparing and contrasting the effectiveness of predictive models in urban and rural settings, where crime patterns and contributing factors may differ significantly<br>(e) There is a need to add the latest research work, on crime predictions as the latest crime predicting techniques mentioned in this research is published in 2021. Whereas, in 2022 and 2023 AI techniques have updated Fastly e–g LLMs introduced |

**Table 2** (continued)

| References | Title | Year published | Gaps |
|---|---|---|---|
| [12] | Crime Prediction Using Machine Learning and Deep Learning: A Systematic Review and Future Directions | 2023 | (a) While the paper covers various global and urban contexts, there is a lack of research emphasizing crime prediction in specific regions or countries. There exists a research gap in the context of crime prediction for countries or regions that have unique socio economic and geographic characteristics, which may impact crime trends differently<br>(b) This paper missed the scheme for including or excluding a paper, this may lead to geographic or temporal bias in paper selection process<br>(c) One important limitation in current research is that not many studies have been covered that used newspapers to predict crime trends. Newspapers provide real-time information about events and crimes<br>(d) Only three databases (IEEE, Science Direct, and ACM) have been searched, Other prominent research document sources have been ignored for example:<br>Google scholar<br>PLOS ONE<br>SpringerLink<br>WileyOnlineLibrary<br>arXiv<br>AIS eLibrary<br>IGI Global<br>Central and Eastern European Online Library |

**Table 2** (continued)

| References | Title | Year published | Gaps |
|---|---|---|---|
| [22] | A survey on societal event forecasting with Deep Learning | 2022 | (a) The study's focus on traditional Machine Learning techniques is a significant limitation. While considering the rapid progress in Deep Learning-based techniques, it is crucial to review recent methods using Deep Learning algorithms for crime predictions to ensure the research is up-to-date and comprehensive<br>(b) The absence of a clear inclusion or exclusion policy is a major flaw in the study. Without defined criteria, the selection process may be biased, potentially excluding important studies and compromising the comprehensiveness and objectivity of the review<br>(c) The paper's coverage of studies may suffer from regional bias. As it is essential to ensure a balanced representation of global studies to avoid skewed findings and provide a comprehensive overview of the field |
| [21] | A Review on Resolving Crime with Prediction | 2021 | (a) The quality of the paper is compromised due to the absence of a systematic approach in selecting research papers. Without a predefined and rigorous methodology, the selection process is prone to bias and subjectivity, making it non-reproducible and likely to exclude significant studies<br>(b) The study fails to explicitly mention the use of advanced learning techniques for crime prediction. Missing this information overlooks significant advancements in the field, leading to an incomplete and potentially outdated review that doesn't fully capture the current state of crime prediction methodologies<br>(c) The study reviewed very few research papers on crime prediction. Despite the abundance of research available, this limited scope means the review fails to encompass the breadth of existing literature, thereby reducing the comprehensiveness and robustness of its conclusion |

review of the recent research in crime prediciton field. This in-depth study will be useful for researchers to understand the latest methods used to predict crimes in different places around the world. We investigated the employed advanced AI models, geographical areas considered for crime records, data sources of crime records, data set types, duration of the crime records, types of crimes that researchers are selecting to perform crimes analysis and predictions. This information can be valuable for the people who work on crime prediction and looking for future endeavors in the field. In Sect. 3 the details of the steps involved in the complete process are presented.

## 3 Methodology

In Sect. 2 some relevant state-of-the-art studies have been critically analyzed to find a comprehensive research gap. In this section, the complete methodology of our research process is presented. In order to provide a clear view a visual block diagram (Fig. 1) depicting the stages of our process is presented. As depicted in Fig. 1, the research process starts with the precise identification of the research objective. This is followed by an extensive and critical review of the existing literature to gain a comprehensive understanding of the current state-of-the-art research work in the field. Through this review, gaps in the existing literature are identified, offering opportunities for further investigation. Subsequently, some well-defined research questions are formulated to address the research objective. A systematic search of databases and repositories is performed, including the construction of purposeful search queries to retrieve relevant research articles. The identified articles are passed through rigorous inclusion and exclusion criteria, resulting in the compilation of a set of related research articles for detail analysis. Finally, the research concludes by synthesizing the findings and contributing to the broader academic discourse. This detailed process is opted by systematically identifying research objectives, conducting a comprehensive literature review, and formulating specific research questions, this method enables the identification of gaps in existing knowledge and provides a structured framework for addressing them. The systematic search of databases and repositories, coupled with stringent inclusion and exclusion criteria, ensures the retrieval of relevant research articles, contributing to the validity and reliability of the study's findings. Each phase of this process is presented one by one in the following sections.

### 3.1 Identifying research objectives

In the recent past, the crime prediction field using spatiotemporal records of past crimes has gained fame. Modern AI, techniques like Deep Learning and transfer learning has emerged as an efficient tool for crime prediction. In literature, crimes in different developed regions of the world are analyzed to predict future crimes using these advanced AI techniques. To explore this research area, we decided to delve into the literature to assess the state-of-the-art studies that have been proposed for crime predictions in different parts of the world. Through this literature analysis, we aim to present the important insights of the previous research work at one place that can help the research community to grab the current trends in the field.

### 3.2 Critical review of the existing literature

Before performing literature review of the advance AI techniques for crime predictions, we conducted an extensive critical review of the exiting literature studies in the field and identified a rigorous research gap that need to be addressed as mentioned in detail in Sect. 2.1. The identified gap in the previous review papers was a motivation for this research to explore the crime prediction techniques in different dimensions. These dimensions are explained in Table 1 in Sect. 1.2.

### 3.3 Formulating research questions

The identified research gap in the literature leads us to investigate the research questions as mention in Table 3.

### 3.4 Targeted repositories

To investigate all the mentioned research questions, the existing state-of-the-art studies have been extracted from various digital repositories by a systematic search process. To search the relevant research articles, digital repositories mentioned in Table 4 have been considered. Although google scholar provide most of the research articles of other repositories, however it can miss some research, therefore, each repository is searched separately by using their own search system.

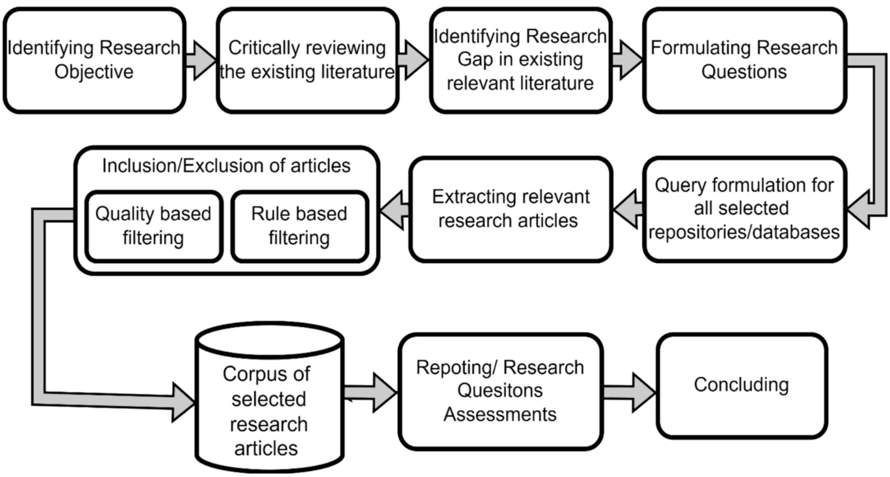



**Fig. 1** Context diagram

### 3.5 Search query

To search the relevant research articles systematically, query terms employed in search queries for differed digital repositories have been listed in Table 5.

All the combinations of selected search terms are employed to extract the maximum relevant research articles as presented in Fig. 2.

To assess the relevant qualitative research articles, all the combinations of search terms have been applied in query string as presented in the Fig. 2. As this query was returning thousands of research articles with bunch of irrelevant papers. To perform a rigorous unbiased search, the query string is restricted to search only articles having search terms in titles only. The query string for google scholar and IEEE Xplore is presented in Table 6. To avoid the review articles, the negation (−) with keywords "review" and "systematic literature review" is added in the query string.

For other repositories, all the combinations of search terms are applied in search boxes provided by each interface one by one.

### 3.6 Inclusion/exclusion criteria

In this systematic literature review, we have designed and implemented a rigorous inclusion and exclusion process to identify and select the most appropriate and high-quality research papers for our analysis. This process is visually depicted in the Fig. 3 which outlines each sequential step of our selection methodology.

As presented in the Fig. 3, the selection process starts with selecting suitable repositories/search engines for relevant research papers. We then use specific search terms to find papers related to our research. Once we have got a bunch of papers, we look at each one to see if it is providing novel approach for predicting crimes, if it does, it is considered for further qualitative analysis. If an article belongs to a book, thesis etc. it was discarded as this study want to analyze only prominent journals and conference academic papers only. After that, we dig into the quality of the research of each selected paper, the quality assessment parameters are explained in the following section,

### 3.7 Quality assessment

To assess the quality of research papers selected in the first phase, we have decided some parameters of quality, for each parameter a score has been defined as described in the Table 7.

The ranking score is assessed using the following research ranking interfaces:

- for journal ranking: Scientific Journal Ranking [24]
- for conference ranking: ICORE Conference Portal [25]

**Table 3** Research questions

| R.Q# | Statement | Objective |
|---|---|---|
| 1 | What are the prominent publication venues that have published recent research on crime prediction using advanced AI techniques? | Identify the primary publication venues where recent research on crime prediction, particularly using advanced AI techniques, has been published. This will help to create a comprehensive overview of the academic platforms and research communities involved in this field |
| 2 | What are the latest developments and advancements in Deep Learning techniques for crime prediction? | To investigate the most recent developments and progress in Deep Learning used for predicting and preventing crimes. This will contribute to an up-to-date understanding of the state-of-the-art techniques in crime prediction |
| 3 | In literature, which geographical area have been focused for crime analysis and prediction using advanced AI techniques? | To systematically investigate the geographical areas that have been focused for crime analysis and prediction utilizing advanced AI techniques. This will help to identify any biases or limitations in the existing research work. Awareness of such biases is crucial for refining and improving AI algorithms, ensuring fair and accurate predictions across a spectrum of geographical contexts |
| 4 | What are the trends and emerging technologies in crime analysis that used real-time data sources and information streams in crime predictive models? | To analyze the trends and emerging technologies in crime analysis, specifically focusing on models that utilize real-time data sources and information streams. This will offer insights into the innovative approaches used in crime prediction, making use of up-to-the-minute data |
| 5 | What types of data sources have researchers commonly utilized in experiments involving crime prediction using advanced AI techniques? | To establish the common data sources frequently used by researchers in experiments involving crime prediction with advanced AI techniques. This will provide a clear picture of the data inputs commonly employed in the field, which can guide future research in this area |
| 6 | What is the range of time spans of crime records used in the literature for crime prediction using advanced AI techniques | To assess the varying time spans utilized in the literature for crime prediction through advanced AI techniques. By scrutinizing these temporal scopes, the objective is to differentiate patterns and correlations, providing insights into the optimal duration of historical crime records that maximizes the effectiveness of AI models in predicting future criminal activities |
| 7 | Which types of crime have been focused on for crime analysis and prediction using advanced AI techniques? | To determine which specific types of crimes have been the primary focus of analysis and prediction using advanced AI techniques. This will help in identifying the areas where AI is most prominently applied in crime prevention |

**Table 4** Digital repositories considered for searching

| Sr. no. | Repository |
|---|---|
| 1 | Google scholar |
| 2 | IEEE Xplore |
| 3 | Springer Link |
| 4 | PLOS ONE |
| 5 | ACM digital library |
| 6 | Willey Online Library |
| 7 | https://arxiv.org/ |
| 8 | AIS eLibrary |
| 9 | IGI Global |
| 10 | Central and Eastern European Online Library |
| 11 | Snowballing |

Each one of the retrieved research papers is ranked as per the score mentioned in Table 7. All the research papers achieving quality score 5 or more have been selected for further detail analysis. The papers achieving quality score less than 5 are discarded.

### 3.8 Parameters to review

To investigate research questions of this study, comprehensive critical analysis is performed, the focused parameters are listed in Table 8.

All the parameters mentioned in Table 8 are extracted from each paper, details of the insights and findings are presented in the Sect. 4.

**Table 5** Selected search terms

| Term | Group 1 | Group 2 | Group 3 |
|---|---|---|---|
| 1 | Crime | Prediction | Deep Learning |
| 2 | Criminal activity | Forecasting | Machine Learning |
| 3 | | Prevention | Neural Network |
| 4 | | | Artificial intelligence |
| 5 | | | AI |

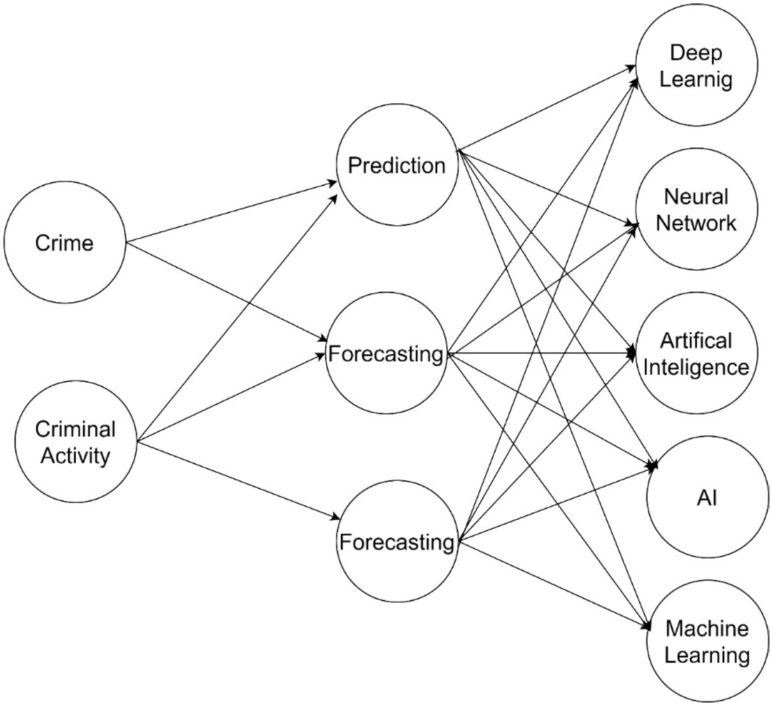



**Fig. 2** Different combinations of search terms

**Table 6** Search queries

| | |
|---|---|
| Google Scholar | intitle:"crime prediction" OR intitle:"criminal activity prediction" OR intitle:"crime forecasting" OR intitle:"crime prevention" AND intitle:"Deep Learning" OR intitle:"neural networks" OR intitle:"Machine Learning"—intitle:"review"—intitle:"Survey"—intitle:"Review"—intitle:"Systematic Literature Review" |
| IEEE Xplore | (("Document Title":crime OR "Document Title":criminal activity) AND ("Document Title":prediction OR "Document Title":forecasting OR "Document Title":prevention) AND ("Document Title":Machine learnig OR "Document Title":Deep Learning OR "Document Title":AI OR "Document Title":Artificial intelligence)) |

## 4 Results and discussion

In Sect. 3 the procedure of this research is discussed in detail. This section presents details of major finding of this comprehensive review in the light of all the research questions mentioned in Table 3. The details of insights are presented in the following subsections.

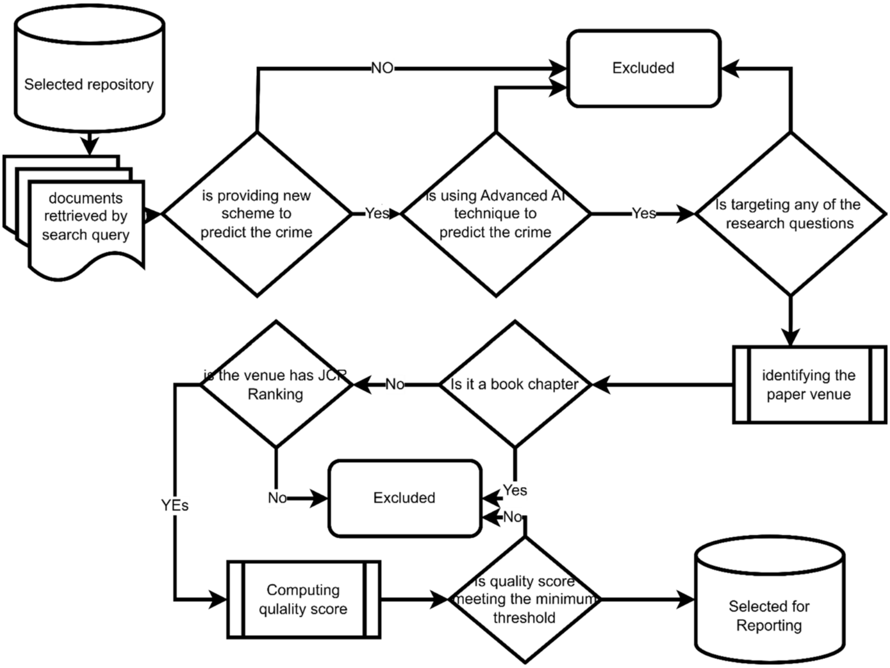



**Fig. 3** Inclusion/exclusion procedure

### 4.1 Dataset collection

The research articles were systematically extracted through a specific query across various digital repositories, with Google Scholar serving as the primary source. However, to ensure comprehensive coverage, additional searches were conducted on individual repositories websites one by one by using their search systems individually. The research articles with published year 2020 to 2023 are extracted. We search the words only in the titles by using the advanced search feature of each digital repositories. The statistics of the search results are mentioned in Table 9.

As presented in first row of the Table 9, from google scholar a total of 143 articles are extracted out of which 43 were selected for further reporting. The remaining rows present the appeared and selected non overlapping articles by the searching interface of each of the repositories under consideration. In total, 172 non-overlapping research documents were obtained from all repositories, and 55 articles were selected for further consideration by fulfilling our selection criteria.

### 4.2 Taxonomy

This study has evaluated the AI-based crime prediction schemes in different perspectives, findings are based on the taxonomy presented in Fig. 4.

**Table 7** Quality assessment parameters

| Feature | Score |
|---|---|
| For predictions of crime, Deep Learning or transfer learning algorithm is used/Not used (As this study is focusing on research articles using modern AI techniques for crime prediction, the research papers using advanced Deep Learning or transfer learning are preferred) | +2/+1 |
| More than one types of crimes have been analyzed yes/no | +1/0 |
| Data collection is presented and data features are explained/not mentioned | +1/0 |
| Complete experimental setup has been presented including the training and testing components of the data/not mentioned | +1/0 |
| Dataset used is available for re-experiments/not available | +1/0 |
| Paper is published in Q-1 ranked journal or CORE A*Conference | +4 |
| Paper is published in Q-2 ranked journal or CORE A Conference | +3 |
| Paper is published in Q-3 ranked journal or CORE B Conference | +2 |
| Paper is published in Q-4 ranked journal or CORE C Conference | +1 |
| Total | 10 |

As presented in the Fig. 4, the crime prediction schemes have been evaluated, in terms of employed predictive algorithm, Geographical area of crime records, dataset type, source of crime records, duration of crime records and types of crime considered. In each theme, there exist a wide array of options employed in literature. The detailed analyses of each of them is presented below.

**Table 8** List of focused parameters

| Sr. no. | Parameter |
|---|---|
| 1 | Title |
| 2 | Publication venue name |
| 3 | Rank of the publishing venue |
| 4 | Publish year |
| 5 | Q-Rank |
| 6 | Is Deep Learning used |
| 7 | Is different types of crimes are considered for prediction |
| 8 | Is data collection presented properly |
| 9 | Is experimental setup presented in detail |
| 10 | Is dataset available to download |
| 11 | Which type of crimes have been considered for experiments |
| 12 | What is the dataset type (historical or runtime) |
| 13 | Which geographical area (city or country) of data is considered |
| 14 | What is the time span of data if historical data used |
| 15 | Which Machine Learning or Deep Learning algorithm is employed to predict crimes |
| 16 | What is the data source (any data repository, police reports, government record, social media or news articles) |
| 17 | What was the evaluation metrics |

### 4.3 Coding scheme

In this study, all the selected papers have been assigned taxonomy codes considering only prominent parameters under consideration. The coding policy is mentioned as follows.

| | | | |
|---|---|---|---|
| Publish year | – Venue type (journal/conference) | – Predictive algorithm | – Region (for which experiments done) |

In the coding process different abbreviations have been used representing various concepts, these abbreviations are explained in Table 10.

### 4.4 Selected papers

In pursuance to explore the research work for AI-driven crime forecasting, the primary criterion for inclusion in our review was the demonstration of a novel approach to predicting crimes using advanced AI techniques. As already mentioned, to ensure the academic integrity of our findings, focusing only on well reputed Journals and conferences, we excluded chapters of books, doctoral dissertations, and thesis work. Subsequently, we delved into the quality of each selected research paper, employing a set of predefined parameters outlined in Table 11. Our quality assessment process utilized research ranking interfaces for both journals and conferences. All the papers were assigned scores based on these parameters, with a maximum achievable score of 10. Only research papers attaining a quality score of 5 or more were deemed suitable for further analysis. The following section provides a comprehensive list of the selected papers that successfully met our selection criteria.

**Table 9** Statistics of extracted papers

| Repository | Total (non-overlapping) search items | Selected |
|---|---|---|
| Google scholar | 143 | 43 |
| IEEE Xplore | 3 | 1 |
| Springer Link | 3 | 2 |
| PLOS ONE | 0 | 0 |
| ACM digital library | 16 | 3 |
| Willey Online Library | 2 | 2 |
| https://arxiv.org/ | 0 | 0 |
| AIS eLibrary | 0 | 0 |
| IGI Global | 1 | 0 |
| Central and Eastern European Online Library | 0 | 0 |
| Snowballing | 4 | 4 |
| Total | 172 | 55 |

### 4.5 List of excluded articles

References of the research articles that appeared in response to the search queries but excluded as they do not full-fill the qualitative selection criteria are presented in Table 12.

### 4.6 Rank-wise paper distribution

As we mentioned in the Fig. 3 that a rigorous quality assessment process is carried out to select top-quality research paper to achieve the research objectives, the ranking wise statistics are presented in the Table 13.

As shown in the Fig. 5, 43% of the papers found from different repositories are published in the top-ranked journals (Q-1), which is the highest rank. Another 27% are in Q-2 journals, the second-highest rank of the journal ranking. Only 11% of papers come from the lowest rank (Q-4), additionally, only 8% of the research articles are from conferences. The large percentage of high-quality

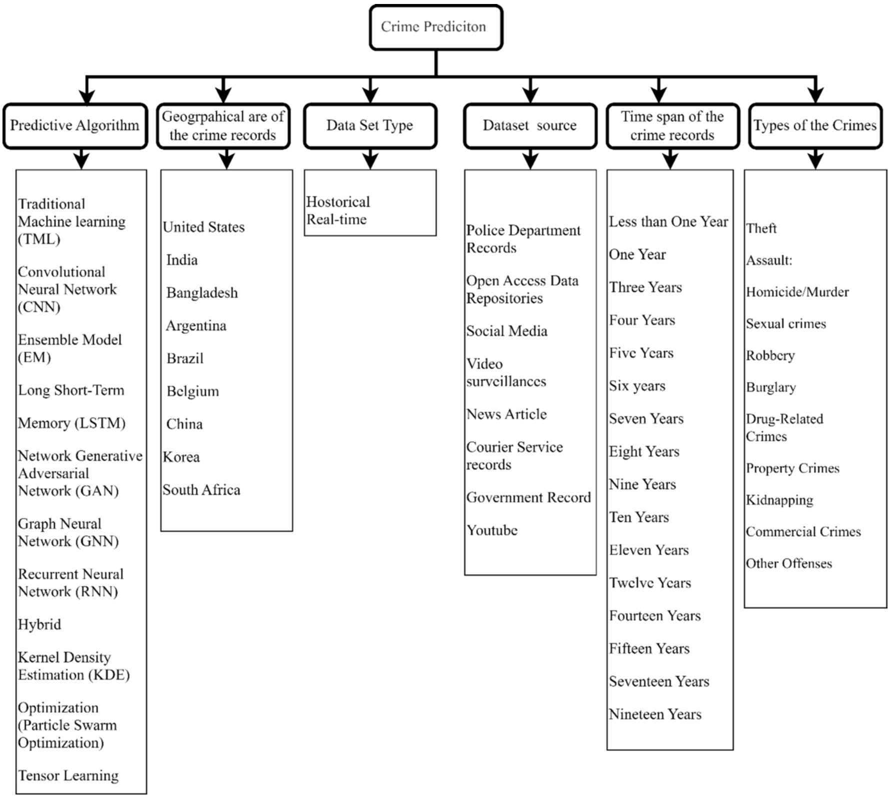



**Fig. 4** Taxonomy

papers in the top ranks venues demonstrates our focus on selecting high-quality research articles for review.

### 4.7 Awarded score-wise distribution

As mentioned in the research protocol Sect. 3.6 all the selected papers have been assigned a quality score. The score wise distribution of the selected papers is mentioned in the Table 14.

As depicted in Table 14 the distribution of quality scores among the selected papers indicates a varied range of evaluations. Many papers earned high scores, with 7 papers achieving a score of 10 out of 10, and 13 papers receiving a score of 9. A notable proportion falls within the range of 8 to 7, with 11 papers each. The statistics are also presented in Fig. 6, depicting the count and percentage of papers based on quality scores. It can be observed that 75% of the selected research papers have a score of 7–10. This distribution highlights the overall high-quality portion of the selected papers, reflecting a thorough evaluation process.

### 4.8 Publishing year-wise distribution

The selected papers are segregated with respect to the year of publishing. This distribution is presented in the Table 15.

Figure 7 presents the distribution of papers across the years, it indicates a notable progression in the research landscape for crime prediction. In 2020, there were 12 papers, followed by a slight increase to 13 in 2021. Subsequently, the research output experienced a significant surge in 2022, reaching 19 papers, reflecting a heightened interest and engagement in the field. However, we can find 12 papers published in 2023.

**Table 10** Abbreviations in codes

| Venue type | Algorithm | Country |
|---|---|---|
| J: Journal | Traditional Machine Learning: TML | United States: US |
| C: Conference | Convolutional Neural Network: CNN | IND: India |
| A: Archive | Recurrent Neural Network: RNN | CHN: China |
| | Long Short-Term Memory: LSTM | BRA: Brazil |
| | Network Generative Adversarial Network: GAN | BNG: Bangladesh |
| | Graph Neural Network: GNN | ARG: Argentina |
| | Ensemble Model: ENM | KRA: Korea |
| | Tensor Learning: TL | |
| | Artificial Neural Network: ANN | |
| | Hybrid (Different): HBD | |

**Table 11** List of selected papers

| Sr | References | Code | Venue name | P. year |
|---|---|---|---|---|
| 1 | [26] | 2021-J-ENM-USA | "IEEE Access" | 2021 |
| 2 | [27] | 2021-J-ENM-USA | "Forecasting" | 2021 |
| 3 | [28] | 2022-J-HBD-USA | "EPJ Data Science" | 2022 |
| 4 | [29] | 2023-J-ENM-USA | "IEEE Access" | 2023 |
| 5 | [30] | 2023-J-CNN-NM | "Bulletin of Electrical Engineering and Informatics" | 2023 |
| 6 | [31] | 2023-J-HBD-USA | "Computers, Environment and Urban Systems" | 2023 |
| 7 | [32] | 2023-J-GNN-USA | "ACM Transactions" on Spatial Algorithms and Systems" | 2023 |
| 8 | [33] | 2023-J-ENM-USA | "Computing and Informatics" | 2023 |
| 9 | [34] | 2021-J-HBD-USA | "Soft computing" | 2021 |
| 10 | [35] | 2022-J-ANN-NM | "Concurrency and Computation Practice and Experience" | 2022 |
| 11 | [36] | 2023-J-ENM-IND | "Multimedia Tools and Applications" | 2023 |
| 12 | [37] | 2022-J-RNN-USA | "Artificial Intelligence" | 2022 |
| 13 | [6] | 2023-J-RNN-USA | "Evolutionary Intelligence" | 2023 |
| 14 | [38] | 2022-J-TML-USA | "Journal of Harbin Institute of Technology (New Series)" | 2022 |
| 15 | [39] | 2022-J-HBD-USA | "ETRI Journal" | 2022 |
| 16 | [40] | 2022-J-ANN-KRA | "ARCHITECTURAL RESEARCH" | 2022 |
| 17 | [41] | 2022-J-TML-BNG | "Journal of Computational Social Science" | 2022 |
| 18 | [42] | 2022-J-LSTM-USA | "Plos One" | 2022 |
| 19 | [43] | 2023-J-HBD-USA | "Computational Intelligence" | 2023 |
| 20 | [44] | 2021-J-CNN-NM | "Multimedia Tools and Applications" | 2021 |
| 21 | [45] | 2020-J-HBD-ARG | "Social Sciences" | 2020 |
| 22 | [46] | 2021-J-TML-IND | "IEEE Access" | 2021 |
| 23 | [47] | 2022-J-TML-CHN | "Computers, Environment and Urban Systems" | 2022 |
| 24 | [48] | 2022-J-TML-IND | "Annals of Data Science" | 2022 |

**Table 11** (continued)

| Sr | References | Code | Venue name | P. year |
|---|---|---|---|---|
| 25 | [49] | 2021-J-TML-NM | "International Journal of Computer and Systems Engineering" | 2021 |
| 26 | [50] | 2022-C-TML-BNG | "International Conference on Information Networking" | 2022 |
| 27 | [51] | 2023-J-GNN-USA | "Signal, Image and Video Processing" | 2023 |
| 28 | [52] | 2022-J-TML-IND | "Karbala International Journal of Modern Science" | 2022 |
| 29 | [53] | 2020-A-CNN-NM | "arXiv preprint" | 2020 |
| 30 | [54] | 2022-J-LSTM-USA | "International Journal of Computer Science & Network Security" | 2022 |
| 31 | [55] | 2022-C-TML-NM | "International Conference on Artificial Intelligence and Pattern Recognition" | 2022 |
| 32 | [56] | 2021-J-TML-SA | "Applied Computational Intelligence and Soft Computing" | 2021 |
| 33 | [15] | 2020-J-LSTM-US | "IEEE access" | 2020 |
| 34 | [57] | 2021-C-TML-US | "International Conference on Artificial Intelligence and Smart Systems (ICAIS)" | 2021 |
| 35 | [58] | 2021-J-TML-US | "GeoJournal" | 2021 |
| 36 | [59] | 2023-J-ENM-US | "Information Sciences" | 2023 |
| 37 | [60] | 2021-J-GAN-US | "Engineering Applications of Artificial Intelligence" | 2021 |
| 38 | [61] | 2020-J-TML-NM | "International Journal of Computer Science and Mobile Computing" | 2020 |
| 39 | [62] | 2020-J-TML-US | "Journal of Engineering Science" | 2020 |
| 40 | [63] | 2020-C-ENM-BRA | "International Conference on Enterprise Information Systems" | 2020 |
| 41 | [64] | 2023-J-LSTM-IND | "SN Computer Science" | 2023 |
| 42 | [3] | 2021-J-TML-US | "IEEE access" | 2021 |
| 43 | [65] | 2020-J-TML-BAL | "Applied Spatial Analysis and Policy" | 2020 |
| 44 | [66] | 2022-J-RNN-US | "CCF Transactions on Pervasive Computing and Interaction" | 2022 |
| 45 | [13] | 2023-J-CNN-IND | "International Journal of Multimedia Information Retrieval" | 2023 |
| 46 | [67] | 2021-J-ANN-US | "ACM Transactions on Internet Technology" | 2021 |
| 47 | [68] | 2022-J-TNL-CHN | "ACM Transactions on Intelligent Systems and Technology" | 2022 |
| 48 | [69] | 2022-J-HBD-US | "Concurrency and Computation" | 2022 |

**Table 11** (continued)

| Sr | References | Code | Venue name | P. year |
|---|---|---|---|---|
| 49 | [16] | 2022-J-ENM-US/CHN | "Neurocomputing" | 2022 |
| 50 | [70] | 2021-J-OT-USA/UAE | "Information Science" | 2021 |
| 51 | [71] | 2020-J-LSTM-CHN | "Data Analysis and Knowledge Discovery" | 2020 |
| 52 | [72] | 2020-J-TML-US | "International Journal of Geographical Information Science" | 2020 |
| 53 | [73] | 2020-J-CNN-US | "Knowledge-Based Systems" | 2020 |
| 54 | [74] | 2020-J-TML-IND | "Journal of Computational and Theoretical Nanoscience" | 2020 |
| 55 | [75] | 2020-J-TML-IND | "International Journal of Digital Crime and Forensics" | 2020 |

**Table 12** List of excluded articles

| References |
|---|
| [7, 12, 18, 37, 76–120, 120–124, 124–139, 139–150, 150] |

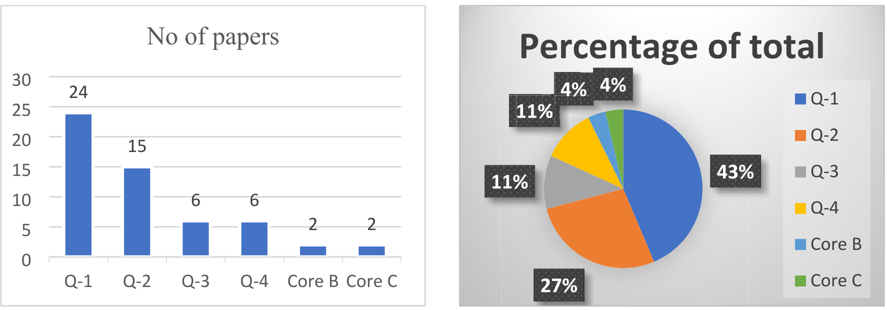
### 4.9 Evaluation metrics-wise distribution

In the detailed review of the selected research articles, we have extracted the types of evaluating metrics. The findings reveal that there exists a wide range of evaluation metrics used in literature to assess the different models. The detailed distribution of the evaluation metrics used is presented below.

As depicted in Table 16, accuracy is the most frequently utilized metric, appearing in 19 papers, highlighting its widespread application in evaluating predictive models. Precision and Recall follow closely, with 10 and 8 occurrences, respectively, underscoring the significance of these metrics in contexts where false positives or false negatives carry distinct consequences. Other commonly employed metrics include Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), highlighting the emphasis on predictive accuracy and precision in quantitative assessments. In addition, specialized metrics such as Precision-Recall Area Under the Curve (PR AUC), and (Mean Average Precision) mAP score present the varied

**Table 13** Rank-wise paper distribution

| Ranking score | No. of papers | References |
|---|---|---|
| Q-1 | 24 | [3, 13, 15, 16, 26–29, 31, 36, 37, 42, 44–47, 59, 60, 68, 70, 72, 73, 151] |
| Q-2 | 15 | [6, 17, 19, 34, 39–41, 48, 51, 56, 64–66, 152] |
| Q-3 | 6 | [14, 35, 54, 69, 71, 153] |
| Q-4 | 6 | [33, 38, 49, 74, 75, 154] |
| Core B | 2 | [50, 55] |
| Core C | 2 | [57, 63] |

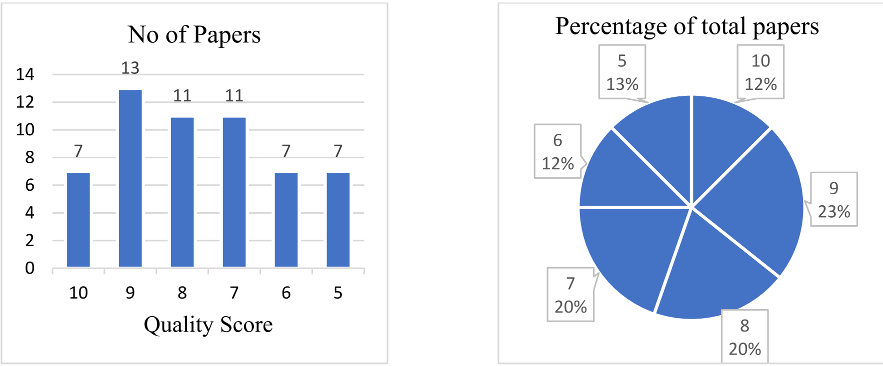



(a) (b)

**Fig. 5** Q-rank-wise papers distribution

**Table 14** Awarded score-wise distribution

| Total score | No of papers | References |
|---|---|---|
| 10 | 7 | [16, 26–29, 37, 42] |
| 9 | 13 | [3, 6, 13, 17, 31, 36, 40, 66–68, 70, 73, 151] |
| 8 | 8 | [14, 19, 34, 39, 44, 58, 72, 155] |
| 7 | 11 | [14, 35, 38, 45, 47, 48, 54, 59, 60, 64, 153] |
| 6 | 7 | [33, 41, 50, 63, 65, 69, 71] |
| 5 | 6 | [49, 53, 55, 74, 75, 154] |




(a) (b)

**Fig. 6** Awarded score-wise papers distribution

needs of different domains, ranging from Machine Learning to advanced real-time detection applications. This comprehensive distribution depicts the variations in model evaluation, where a combination of metrics is often necessary for a comprehensive understanding of performance.

### 4.10 Assessment of research questions

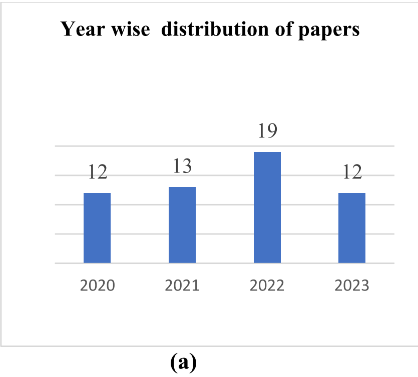
All the findings regarding insights of the selected research articles are summarized considering the research questions as presented in the following sections.

#### 4.10.1 Assessment of first research question

In response to our first research question, “What are the prominent publication venues that have published recent research on crime prediction using advanced AI techniques?”, the research findings span a diverse range of venues, describing the

**Table 15** Publishing year-wise distribution

| Year | No. of papers | References |
|---|---|---|
| 2020 | 12 | [15, 45, 53, 63, 65, 71–75, 151, 154] |
| 2021 | 13 | [3, 26, 27, 34, 44, 46, 49, 56, 57, 60, 67, 70, 152] |
| 2022 | 19 | [16, 28, 35, 37–42, 47, 48, 50, 54, 55, 66, 68, 69, 153] |
| 2023 | 12 | [6, 13, 14, 17, 19, 29, 31, 33, 36, 51, 59, 64] |



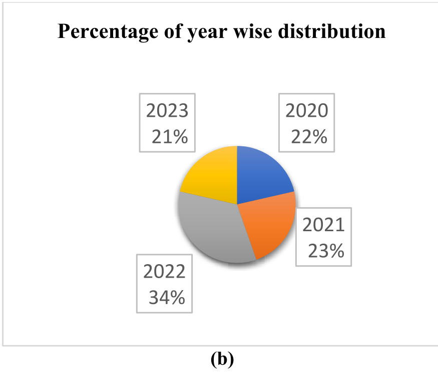




**Fig. 7** Year-wise distribution of papers

interdisciplinary nature of crime prediction studies. Publishing venue wise distribution of papers is shown in Table 17.

As presented in Table 17, the selected papers are published across a spectrum of journals and conferences, such as IEEE Access, Forecasting, EPJ Data Science, ACM Transactions on Spatial Algorithms and Systems, and more. IEEE Access is the only journal that has maximum frequency of papers for crime prediction, rest all venues have one or two papers. This broad distribution reflects the engagement of researchers in various academic domains, contributing to the evolving landscape of crime prediction literature.

#### 4.10.2 Assessment of second research question

This section presents the findings against our second research question “What are the latest developments and advancements in Deep Learning techniques for crime prediction?”. Table 18 presents a detailed overview of various AI algorithms utilized in recent advancements of Deep Learning techniques for crime prediction.The Traditional Machine Learning (TML) methods like Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, K-Nearest Neighbors (KNN) Decision Tree, and Random Forest were accounting for 32.14% (18 instances), Convolutional Neural Networks (CNN) appearing in 10.71% (6 studies), and Hybrid Models explored in 25.00% (14 papers). Ensemble Models (EM) are represented in 5.36% (3 instances),

**Table 16** Evaluation-metrics wise distribution

| Metrics | No. of papers | References |
|---|---|---|
| Accuracy | 19 | [13, 15, 16, 26, 29, 34, 40, 44, 46, 50, 51, 53, 54, 57, 67–70, 75] |
| Precision | 10 | [26, 34, 36, 46, 49, 50, 55, 57, 65, 70] |
| Recall | 8 | [26, 34, 36, 46, 50, 55, 57, 70] |
| F1-score | 3 | [26, 27, 65] |
| PR AUC (Precision-Recall Area Under the Curve) | 1 | [27] |
| (Receiver Operating Characteristic Area Under the Curve) | 1 | [27] |
| mAP score (mean Average Precision) | 4 | [14, 31, 48, 52] |
| Inference speed (FPS—Frames Per Second) | 2 | [14, 17] |
| Mean Absolute Error (MAE) | 7 | [3, 37, 45, 64, 66, 67, 69] |
| Root Mean Squared Error (RMSE) | 8 | [6, 37, 64, 67–69, 71, 72] |
| Forecasting error | 1 | [6] |
| Mean Squared Error (MSE) | 2 | [6, 66] |
| Adjusted R squared | 2 | [48, 52] |
| Mean Absolute Percentage Error (MAPE) | 2 | [48, 52] |
| G_mean | 1 | [55] |
| Area Under the Receiver Operating Characteristic curve (AUC-ROC) | 1 | [15] |
| Area Under the Precision-Recall curve (AUC-PR) | 1 | [15] |
| Average root mean square error (aRMSE) | 1 | [39] |
| Percentage root mean square error (PRMSE) | 1 | [71] |
| Bayesian Information Criterion (BIC) | 1 | [152] |
| Jarque–Bera (JB)/Prob (JB) | 2 | [151, 154] |
| Assertiveness rates | 1 | [63] |
| Root mean square deviation | 1 | [63] |
| Near-hit rate | 1 | [65] |

**Table 16** (continued)

| Metrics | No. of papers | References |
|---|---|---|
| Pearson Correlation Coefficient (PCC) | 1 | [72] |
| Predictive Accuracy Index (PAI) | 1 | [72] |
| Predictive Efficiency Index (PEI) | 1 | [72] |
| Jensen-Shannon divergence | 1 | [73] |
| Structure Similarity Index (SSIM) | 1 | [73] |

while Long Short-Term Memory (LSTM), Graph Neural Networks (GNN), and Recurrent Neural Networks (RNN) each feature in 3.57% (2 articles). Other techniques, such as Generative Adversarial Networks (GAN), Kernel Density Estimation (KDE), Optimization, and Tensor Learning, are each mentioned once, constituting 1.79% each.

Among the Hybrid Models, diverse combinations were explored. Notable hybrid algorithm combinations include DeCXGBoost, a fusion of Convolutional Neural Network (CNN) and XGBoost, 2DCONV-LSTM incorporating 2D convolution and long short-term memory neural network, and CLSTM-NN, which integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory networks. Additionally, various other combinations such as SARIMA and Artificial Neural Network (ANN), HDBSCAN for hotspot detection paired with SARIMA for overall crime prediction, and the Dual-robust Enhanced Spatial–temporal Learning Network (DuroNet) presents the inventive fusion of different models for enhanced predictive capabilities. This emphasis on hybridization underscores a trend in the field towards integrating diverse Deep Learning techniques to address the complexities inherent in crime prediction scenarios.

#### 4.10.3 Assessment of third research question

The findings in response to our 3rd research question "Which geographical area have been focused for crime analysis and prediction using advanced AI techniques?" are depicted in Table 19. This table presents a notable concentration in various cities across the United States. Chicago emerges as the most prominently focused city, with 13 articles dedicated to crime analysis and prediction within its urban context. New York City follows closely with 7 articles, while other major U.S. cities such as Baltimore, Boston, and Philadelphia also been used for crime prediction experimentation.

To discuss a broader perspective, this study analyzes the region or country-wise distribution of the research articles, this distribution is reflected in Table 20. The review found a significant dominance of United States as 31 (56%) papers have used the dataset from US. This high frequency underscores a strong emphasis on American urban environments in the application of advanced AI techniques for crime-related research, suggesting a concentrated effort to address complex crime challenges within these metropolitan areas. In addition to the United States, India emerges as second region for crime analysis, with 6 articles using dataset from this country, three of the research papers have utilized crime record from China. Furthermore, research extends to various countries, including Bangladesh, Argentina, Brazil, Belgium, and Korea with only one paper for each. One of the notable points is that despite its unique and challenging blend of economic, geographical, political, and social factors, no research articles specifically address crime analysis within Pakistani cities. This absence raises interesting questions about the potential applicability and effectiveness of advanced AI techniques in the Pakistani context, where distinct socio-cultural dynamics and regional

**Table 17** Publishing venue-wise distribution of papers

| Sr. no. | Venue name | No. of papers |
|---|---|---|
| 1 | IEEE Access | 5 |
| 2 | Forecasting | 1 |
| 3 | EPJ Data Science | 1 |
| 4 | Bulletin of Electrical Engineering and Informatics | 1 |
| 5 | Computers, Environment and Urban Systems | 1 |
| 6 | ACM Transactions on Spatial Algorithms and Systems | 1 |
| 7 | Computing and Informatics | 1 |
| 8 | Soft computing | 1 |
| 9 | Concurrency and Computation Practice and Experience | 1 |
| 10 | Multimedia Tools and Applications | 1 |
| 11 | Artificial Intelligence | 1 |
| 12 | Evolutionary Intelligence | 1 |
| 13 | Journal of Harbin Institute of Technology (New Series) | 1 |
| 14 | International Journal of Pattern Recognition and Artificial Intelligence | 1 |
| 15 | ETRI Journal | 1 |
| 16 | Architectural Research | 1 |
| 17 | Journal of Computational Social Science | 1 |
| 18 | Plos One | 1 |
| 19 | Computational Intelligence | 1 |
| 20 | Multimedia Tools and Applications, | 1 |
| 21 | Social Sciences | 1 |
| 22 | Computers, Environment and Urban Systems | 1 |
| 23 | Annals of Data Science | 1 |
| 24 | International Journal of Computer and Systems Engineering, | 1 |
| 25 | International Conference on Information Networking | 1 |
| 26 | Signal, Image and Video Processing | 1 |
| 27 | Karbala International Journal of Modern Science | 1 |
| 28 | arXiv preprint | 1 |
| 29 | International Journal of Computer Science & Network Security | 1 |
| 30 | International Conference on Artificial Intelligence and Pattern Recognition | 1 |
| 31 | Applied Computational Intelligence and Soft Computing | 1 |
| 32 | International Conference on Artificial Intelligence and Smart Systems (ICAIS) | 1 |
| 33 | GeoJournal | 1 |
| 34 | Information Sciences | 2 |
| 35 | Engineering Applications of Artificial Intelligence | 1 |
| 36 | International Journal of Wireless and Mobile Computing | 1 |
| 37 | Journal of Engineering Science | 1 |
| 38 | International Conference on Enterprise Information Systems | 1 |
| 39 | SN Computer Science | 1 |
| 40 | Applied Spatial Analysis and Policy | 1 |
| 41 | CCF Transactions on Pervasive Computing and Interaction | 1 |
| 42 | International Journal of Multimedia Information Retrieval | 1 |

**Table 17** (continued)

| Sr. no. | Venue name | No. of papers |
|---|---|---|
| 43 | ACM Transactions on Internet Technology | 1 |
| 44 | ACM Transactions on Intelligent Systems and Technology | 1 |
| 45 | Concurrency and Computation | 1 |
| 46 | Neurocomputing | 1 |
| 47 | Data Analysis and Knowledge Discovery | 1 |
| 48 | International Journal of Geographical Information Science | 1 |
| 49 | Knowledge-Based Systems | 1 |
| 50 | Journal of Computational and Theoretical Nanoscience | 1 |
| 51 | International Journal of Digital Crime and Forensics | 1 |

**Table 18** Predictive algorithm-wise distribution

| Theme | Class | No. of papers | References |
|---|---|---|---|
| Algorithm used | Traditional Machine Learning (TML) | 18 | [26, 35, 38, 41, 45, 47–50, 52, 55–57, 59, 69, 72, 151, 152, 154] |
| | Convolutional Neural Network (CNN) | 6 | [13, 14, 34, 35, 44, 53] |
| | Ensemble Model (EM) | 3 | [28, 46, 65] |
| | Long Short-Term Memory (LSTM) | 2 | [54, 71] |
| | Network Generative Adversarial Network (GAN) | 1 | [60] |
| | Graph Neural Network (GNN) | 2 | [17, 51] |
| | Recurrent Neural Network (RNN) | 2 | [6, 66] |
| | Hybrid | 14 | [3, 15, 16, 19, 27, 29, 31, 33, 39, 42, 63, 64, 69, 73, 75] |
| | Kernel Density Estimation (KDE) | 1 | [74] |
| | Optimization (Particle Swarm Optimization) | 1 | [70] |
| | Tensor Learning | 1 | [68] |

challenges exist. Addressing this deficiency could contribute valuable insights for policymakers and law enforcement agencies in Pakistan.

#### 4.10.4 Assessment of fourth research question

Answering the research question-4, regarding usage of real-time data for crime prediction. Only one research paper used real-time data for crime prediction using CCTV video surveillance reference as mentioned in Table 21. Most studies focused on looking at historical data rather than using current information. This suggests that there is room for more research and innovation in the field, especially when it comes to incorporating real-time data into crime prediction models. This gap indicates an opportunity for

**Table 19** City-of-dataset-wise distribution of papers

| City name | References | No. of papers |
|---|---|---|
| Chicago—United States | [17, 19, 26, 28, 29, 31, 34, 37–39, 51, 67, 151] | 13 |
| Los Angeles—United States | [26] | 1 |
| District of Columbia—United States | [27] | 1 |
| Minneapolis—United States | [28, 31] | 2 |
| Philadelphia—United States | [34, 60] | 2 |
| San Francisco—United States | [49, 73] | 2 |
| Baltimore—United States | [15, 28, 31] | 3 |
| Austin—United States | [28, 31] | 2 |
| New York City—United States | [3, 17, 37, 42, 66–68] | 7 |
| Boston—United States | [33, 54, 152] | 3 |
| Denver city—United States | [57] | 1 |
| India—India | [36, 46, 48, 64, 74, 75] | 6 |
| Sacramento—United States | [6] | 1 |
| Dhaka—Bangladesh | [41] | 1 |
| Buenos Aires—Argentina | [45] | 1 |
| ZG City, a coastal city in Southeast China | [47] | 1 |
| Sao Paulo—Brazil | [63] | 1 |
| Belgian city—Belgium | [65] | 1 |
| Allahabad—India | [13] | 1 |
| Xiaogan—China | [68] | 1 |
| Seoul—Korea | [40] | 1 |
| Not mentioned (NM) | [14, 35, 44, 53, 69, 154] | 1 |

future studies to explore how using real-time information can improve the accuracy and timeliness of predicting crimes. By addressing this gap, researchers can contribute to developing more effective and responsive crime prevention strategies, keeping up with the advancements in technology and the increasing availability of real-time data.

#### 4.10.5 Assessment of fifth research question

In dealing with the fifth research question "What types of data sources have researchers commonly utilized in experiments involving crime prediction using advanced AI techniques?" The investigation reveals a diverse landscape, drawing from various options such as police department records, government records, open-access repositories, social media, and news articles. The Table 22 provide a concise distribution of the multiple sources through which datasets are harnessed for predictive models in crime analysis.

As depicted in Table 22, open access data repositories appeared as the most frequently utilized data source, featuring in 22 papers, representing the significance of publicly available datasets in crime analysis research. Police department records

**Table 20** Country wise distribution

| Country for which experiments done | Country | References |
|---|---|---|
| | United States | [3, 6, 15–17, 19, 26–29, 31, 33, 34, 37–39, 42, 49, 51, 54, 59, 60, 66–68, 70, 72, 73, 151, 152] |
| | India | [13, 52, 70, 74, 75] |
| | Bangladesh | [41, 50] |
| | Argentina | [70] |
| | Brazil | [65] |
| | Belgium | [63] |
| | China | [16, 55, 71] |
| | Korea | Lee et al. (2022) |
| | South Africa | [56] |

being second represent a prominent source, with 13 papers relying on official law enforcement data. Government records also play a substantial role, appearing in eight papers. On the other hand, data sets for News articles appear in three papers, indicating the recognition of non-traditional sources in crime analysis. Social media and video surveillance, while less prevalent, contribute to two and one paper(s) respectively, highlighting the growing influence of digital and visual data in the field. Additionally, the incorporation of YouTube videos in one instance reflects the expanding spectrum of data sources explored.

#### 4.10.6 Assessment of sixth research question

The length of time duration of historical data for crime prediction is very important as the chosen length of the time span significantly influences the accuracy and applicability of advanced AI models in predicting crime trends. Therefore, in this study we aimed to analyze the research articles in pursuance of our 6th research question "What is the range of time spans used in the literature for crime prediction using advanced AI techniques", Table 23 shows the frequency of papers that used historical data for different time duration. The first column presents the time duration for which criminal instances have been used for crime prediction, the second column shows references and the third column provides the frequency of papers.

As shown in the Table 23, most of the papers, constituting 8 instances, are characterized by a data collection period of three years. Following this, there is a notable prevalence of research spanning one year, with 5 papers falling into this category.

**Table 21** Papers using realtime data

| Data type | Reference |
|---|---|
| Real time | Sung and Park (2021) |

Additionally, a cluster of 2 papers each is associated with datasets covering four, five, seven, and eight years. A single paper each corresponds to datasets of less than one year, six years, nine years, ten years, eleven years, twelve years, fourteen years, fifteen years, seventeen years, and nineteen years. This variation in dataset durations underscores the breadth of temporal considerations in research for crime prediction. However, we can deduce that in literature, for crime prediction, data set of 3 years' time span is considered most frequently for analysis.

#### 4.10.7 Assessment of seventh research question

In pursuance to our seventh research question "Which types of crime have been focused for crime analysis and prediction using advanced AI techniques?" We extracted the types of crime that had been considered for prediction. This study reveals that there exists a diverse array of crime types considered for experiments. As the researcher have used different synonyms terms for the same type of crimes, all the used terms are merged into groups as presented in Table 24. A majority of research papers did not explicitly mention the types of crimes, they all are incorporated in a separate group as "crime".

The crime type distribution considering the broader categories of crimes is presented in Table 25.

As presented in Table 25, the distribution of papers across various crime types reveals distinct patterns in research priorities. Theft and assault appeared as the most extensively considered categories, each accounting for 18 (33%) papers, indicating a significant emphasis on understanding and predicting these criminal activities. Homicide/murder and sexual crimes follow closely, with 8 and 4 papers, respectively, reflecting the research community's interest in addressing these types of violent offenses. Burglary and property crimes receive notable attention, with 9 and 7 papers, respectively, suggesting a recognition of the importance of safeguarding homes and possessions. Robbery and drug-related crimes are also explored, with 7 and 6 papers, highlighting the significance of understanding criminal behavior

**Table 22** Data source-wise distribution of papers

| Data source | References | Total papers |
|---|---|---|
| Police department records | [3, 29, 33, 42, 49–51, 54, 65, 66, 72, 152, 154] | 13 |
| Open access data repositories | [6, 14–17, 26–28, 31, 34, 35, 37, 39, 45, 56, 57, 59, 63, 68, 69, 73, 151] | 22 |
| Social media | [64, 67] | 2 |
| Video surveillances | [67] | 1 |
| News article | [70, 74, 75] | 3 |
| Courier service records | [13, 44, 55] | 3 |
| Government record | [19, 36, 41, 46–48, 52, 60] | 8 |
| Youtube | [53] | 1 |
| Not mentioned | [71] | 1 |

**Table 23** Time-duration-wise distribution

| Time duration | References | No. of papers |
|---|---|---|
| Less than one year | [19] | 1 |
| One year | [17, 28, 31, 60, 74, 75] | 5 |
| Three years | [6, 16, 45, 47, 49, 54, 68, 152] | 8 |
| Four years | [51, 59] | 2 |
| Five years | [27, 65] | 2 |
| Six years | [57] | 1 |
| Seven years | [42, 50] | 2 |
| Eight years | [36, 48] | 2 |
| Nine years | [3] | 1 |
| Ten years | [63, 70] | 2 |
| Eleven years | [40, 52, 56] | 3 |
| Twelve years | [60] | 1 |
| Fourteen years | [34, 46] | 2 |
| Fifteen years | [38, 73] | 2 |
| Seventeen years | [39] | 1 |
| Nineteen years | [26] | 1 |

related to these activities. Kidnapping, commercial crimes, and other offenses have a comparatively lower representation, Notably, 25 (45%) papers fall under the general category of "Crime," emphasizing the prevalence of studies that encompass a broader spectrum of criminal activities. In summary, the research landscape in this domain is diverse, with a notable emphasis on theft, assault, and related offenses. Section 5 presents the conclusion of the findings of this study.

### 4.11 Summary of the findings

The detailed analysis under the light of all research questions can be summarized as follows. The review highlights the interdisciplinary nature of the field, with prominent publications like IEEE Access leading the discourse. Emerging AI methods, such as Convolutional Neural Networks, Generative Adversarial Networks, and Graph Neural Networks, complement traditional Machine Learning approaches, reflecting methodological innovation. Geographically, many studies focus on U.S. cities, particularly Chicago, while research on underdeveloped regions remains under-explored. Only one study, all the papers emphasized historical data except one that integrated real time data using CCTV videos. Data sources include police and government records, open-access repositories, and unconventional platforms like social media and news. The temporal span of crime records varies widely, with most studies analyzing three years of data but others extending to over a decade. Commonly studied crimes include theft, assault, homicide, and sexual offenses.

**Table 24** Types of crime

| Broader crime type | Merged terms (actual term used in papers) |
|---|---|
| Theft | Theft, Motor vehicle theft, Larceny-theft, Petit larceny, Grand larceny, Shoplifting, and Vehicle theft |
| Assault | Assault, Aggravated assault, Felony assault |
| Homicide/Murder | Homicide, Murder, Rapid trial |
| Sexual crimes | Sex abuse, Forcible rape, and Rape |
| Robbery | Robbery |
| Burglary | Burglary, Home burglary, and Trespass |
| Drug-Related Crimes | Narcotics and Juvenile crime due to drug addiction |
| Property Crimes | Arson, Criminal damage, Fraud, Gambling, Pickpocketing, Vehicle damage |
| Kidnapping | Kidnapping, False imprisonment |
| Commercial Crimes | Counterfeit cigarette crime |
| Other Offenses | Cybercrime, Death caused by negligence, Repression of women and children, Street robberies, Traffic offenses, and Eating and damaging |

**Table 25** Crime type-wise distribution

| Broader crime type | No. of papers | References |
|---|---|---|
| Theft | 18 | [13, 16, 17, 27–29, 31, 36, 40, 42, 45–48, 53, 68, 71] |
| Assault | 18 | [13, 14, 16, 17, 27–29, 31, 36, 37, 42, 48, 53, 59, 68, 72, 74, 151] |
| Homicide/Murder | 8 | [27, 36, 45, 46, 48, 50, 151, 154] |
| Sexual crimes | 4 | [27, 36, 46, 151] |
| Robbery | 7 | [27, 37, 45, 59, 72, 151, 154] |
| Burglary | 9 | [16, 17, 27, 37, 42, 59, 65, 68, 74] |
| Drug-Related Crimes | 6 | [17, 36, 37, 41, 50, 59] |
| Property Crimes | 7 | [16, 17, 27, 28, 31, 68, 74] |
| Kidnapping | 2 | [151, 154] |
| Commercial Crimes | 1 | [55] |
| Other Offenses | 2 | [74, 75] |
| Crime | 25 | [3, 6, 19, 26, 33–35, 38, 39, 44, 49, 51, 52, 54, 56, 57, 60, 63, 64, 66, 67, 69, 70, 73, 152] |

## 5 Discussion

After a detailed study of the reviewed literature, it is evident that AI-based crime prediction models hold the promise of revolutionizing smart policing in the digital era. Advanced techniques like CNNs, LSTMs, GNNs, GANS and hybrid models enable law enforcement agencies to analyze crime patterns, identify high-risk areas, and allocate resources more strategically. These tools mark a shift from reactive to proactive policing by providing the means to predict and prevent crimes before they occur. Furthermore, in the context of increasingly digitized urban environments, AI models can integrate with smart city technologies, such as IoT-enabled CCTV systems, to process real-time data. This integration has the potential to enhance situational awareness, improve response times, and adapt policing strategies to rapidly changing conditions, ensuring more effective and adaptive law enforcement practices.

In addition to operational improvements, AI aligns with the broader objectives of modern policing by fostering transparency, enabling proactive approaches, and strengthening community trust. For instance, AI-driven predictive dashboards can provide actionable insights into crime hotspots, allowing law enforcement agencies to design and communicate targeted prevention strategies. Sharing such insights with the public through transparent platforms can encourage community collaboration and build trust. However, as policing increasingly relies on digital tools, equipping officers with the necessary training to interpret and apply AI-generated insights will be critical. This shift toward technology-driven policing not only enhances safety but also fosters community-focused strategies that align with public expectations in the digital age. In this context, AI emerges as a transformative enabler of smarter and more equitable crime prevention.

### 5.1 Identified limitations

After critically analyzing the findings and insights, the following limitations in the existing literature have been identified, along with recommendations for future work.

#### 5.1.1 Limited use of real-time data

The analysis reveals that only one study incorporated real-time data, specifically using CCTV video surveillance, while the majority relied solely on historical data. This over-reliance on static datasets limits the potential benefits of dynamic and up-to-date information, which can significantly enhance situational awareness and enable faster responses to emerging incidents. Real-time data integration offers opportunities for predictive models to adjust dynamically, improving both their accuracy and timeliness. It also supports the creation of early warning systems, which can play a pivotal role in crime prevention. However, implementing real-time data integration poses challenges, including the need for robust technological infrastructure, addressing privacy concerns, and ensuring the reliability of data streams. Future research should explore strategies to overcome these barriers and unlock the full potential of real-time AI-driven crime prediction systems.

#### 5.1.2 Dataset quality, bias, model generalizability and ethical concerns

A comprehensive analysis of the literature reveals significant challenges in the geographical scope, data quality, and fairness of AI-driven crime prediction models. A predominant focus on cities in developed nations, particularly within the United States, has resulted in geographical bias that limits the applicability of these models across diverse cultural, socioeconomic, and regional contexts. Models trained on crime records from specific regions may not perform well when applied to other areas due to variations in the nature and frequency of crimes. External factors such as socioeconomic conditions [156–158], demographics [159], climate [160, 161], and cultural practices severely effect the crime trends and frequencies. For instance, crime trends in high-income urban areas differ significantly from those in low-income rural regions, creating disparities in model performance.

The problem is further compounded in underdeveloped nations, where systematic data collection is often sparse, incomplete, or inconsistent. Differences in data availability, reporting mechanisms, and policing practices exacerbate the challenges of building reliable and generalizable AI models. The reliance on biased or incomplete datasets can lead to inaccurate predictions, ineffective resource allocation, and ethical concerns. For example, biased models may disproportionately target marginalized communities, overlook evolving crime patterns, and reinforce systemic discrimination, ultimately undermining public trust in predictive technologies.

To address these challenges, future research must prioritize the development of fair, adaptable, and globally applicable AI models. This involves designing algorithms capable of identifying and mitigating data biases to ensure equitable predictions across diverse socio-economic and demographic contexts. Efforts should also focus on creating standardized, high-quality datasets that represent a broader range of regions and communities. Furthermore, addressing the ethical implications of deploying biased models is essential. Transparent methodologies and accountability mechanisms must be implemented to foster public trust, promote fairness, and avoid exacerbating social inequalities.

**Data Availability Statement** No data associated in the manuscript.

## Declarations

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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