Spatio-Temporal Crime HotSpot Detection and Prediction: A Systematic Literature Review

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ABSTRACT The primary objective of this study is to accumulate, summarize, and evaluate the state-of-the-art for spatio-temporal crime hotspot detection and prediction techniques by conducting a systematic literature review (SLR). The authors were unable to find a comprehensive study on crime hotspot detection and prediction while conducting this SLR. Therefore, to the best of author's knowledge, this study is the premier attempt to critically analyze the existing literature along with presenting potential challenges faced by current crime hotspot detection and prediction systems. The SLR is conducted by thoroughly consulting top five scientific databases (such as IEEE, Science Direct, Springer, Scopus, and ACM), and synthesized 49 different studies on crime hotspot detection and prediction after critical review. This study unfolds the following major aspects: 1) the impact of data mining and machine learning approaches, especially clustering techniques in crime hotspot detection; 2) the utility of time series analysis techniques and deep learning techniques in crime trend prediction; 3) the inclusion of spatial and temporal information in crime datasets making the crime prediction systems more accurate and reliable; 4) the potential challenges faced by the state-of-the-art techniques and the future research directions. Moreover, the SLR aims to provide a core foundation for the research on spatio-temporal crime prediction applications while highlighting several challenges related to the accuracy of crime hotspot detection and prediction applications.

INDEX TERMS Crime patterns, spatio-temporal crime prediction, spatio-temporal HotSpot detection, SLR.

I. INTRODUCTION

Security is an essential aspect of strengthening the roots of a country. It is the responsibility of law enforcement agencies of a country to control the crime incidents and crime threats for the betterment of the society. Crimes can make a significant impact on the economic growth of a country. Therefore, countries are spending a substantial amount of their gross domestic product (GDP) on law enforcement agencies to control crimes [1], [2]. Advancement in technology, especially Geographical information systems (GIS), assisted the researchers in presenting numerous crime detection and prediction techniques.

The data of enormous volume being available in the past few years to have led the scientists with the motivation for pursuing research in the field of crime and criminal investigations. Studying the crime trends and patterns have been the priority of the law enforcement agencies to make an effective policy by using the historical data to make a peaceful community [3], [4]. Based on historical data, forecasting crimes has been a subject of interest that gained much attention in research, which resulted in proposing a significant number of different methods for the discovery of different aspects related to crime prediction [5], [6], and [7].

Crime can be considered as a location-oriented feature as some places can exhibit greater risk of crime to be committed than others [8]. It is an understood fact that in a particular area, no matter the size, crime is not distributed evenly, uniformly, or even randomly within that area or city [9]. In this regard,

mapping of crime hotspots can help understand the reasons behind the frequent occurrence of crimes in those areas. Therefore, the insights and knowledge regarding the mapping of crimes are of significant importance for citizens. Different types of crimes and the full consideration of the protection and safety of citizens in any society are significant components that play a vital role directly in the quality of the lives of residents. Certain types of criminal incidents such as larceny, identity theft, or even pick-pocketing can cause disturbance and stress in an individual's life and affect his mental peace. Criminology develops and studies different theories regarding criminal behavior from different perspectives to address these issues. Numerous types of crimes can occur in an area with different frequencies. An area may be flagged for higher pick-pocketing events while the other for a particular type of crime; hence it is understood from Newyork City (NYC) crime data[1] that the frequency of different types of crimes is not uniformly distributed. Fig. 1 shows the occurrence of varying crime types along with the frequency.
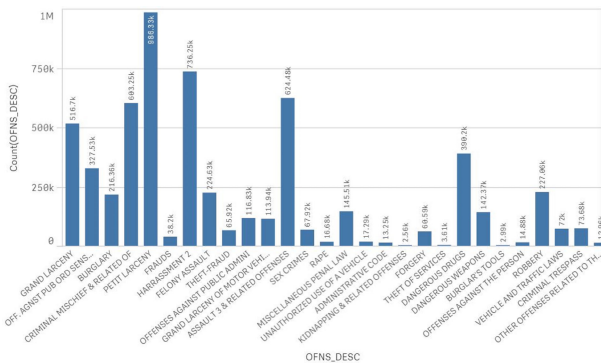

FIGURE 1. Frequency distribution of different criminal events in New York City (NYC).

The inclusion of spatial and temporal information in the crime datasets using GIS has revolutionized the crime prediction systems [10]. The spatio-temporal information helps the researchers to present more reliable and accurate crime prediction systems. Moreover, time series analysis techniques such as ARIMA, Moving Averages (MA), and Exponential Smoothing (ES) performs exceptionally well in crime forecasting [11], [12]. Besides, deep learning techniques such as CNN and LSTM has also been explored and found to be useful as compared to state-of-the-art techniques [13], [14]. However, to strengthen the crime prediction system, a sufficient amount of data is required. Researchers around the globe are continuously pursuing different paradigms such as transfer learning to improve the crime prediction accuracy [15] significantly.

In the literature, many researchers have investigated the use of machine learning and time series analysis techniques to assure the accuracy and reliability of crime prediction systems [12]. Some papers have emphasized on the

[1]https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Historic/qgea-i56i/data

significance of spatial and temporal information to find irregularities in crime [16], [17]. Shamsuddin *et al.* [18] presented the first comprehensive overview of prediction methods used for crime prediction. Notably, they focus on the clustering, time series analysis, and deep learning approaches. Besides, the majority of researchers survey data mining and machine learning techniques for crime detection and prediction [19]–[22]. Kapoor *et al.* [23] present analysis of crime dataset and enlighten on the essential features such as spatial and temporal features. Helbich and Leitner [24] published an editorial on the practical significance of spatial and Spatio-temporal information for crime analytics. Although the authors presented different survey papers on crime analysis, the main focus has been on exploring the use of data mining techniques.

Furthermore, only a single author has focused on the crime dataset, which is one of the fundamental element in crime prediction system. Besides, the literature on crime prediction techniques and challenges is still scattered that obstruct the innovation of advance technologies and new ideas for crime prediction. Therefore, a systematic analysis of crime detection and prediction is inevitable. In this article, we provide a comprehensive literature review of data mining and machine learning approaches and spatio-temporal datasets, potential challenges faced by existing literature, and proposed potential research areas. In summary, the significant contribution and why SLR is necessary is presented in the following sections:

A. PROBLEM STATEMENT

Crime hotspot identification and prediction is an essential area of research to oversee criminal activities for the law and enforcement agencies. A vast amount of literature has been cited to identify and predict criminal hotspots in Spatio-temporal context. However, it is difficult to review the available shreds of evidence based on traditional literature. The scattered research produced and cited motivated the need for a systematic literature review (SLR) on Spatio-temporal crime hotspot identification and predicting.

The aim is to systematically review and report the available pieces of evidence in the current literature to support the proposed research questions. This research organizes and sums up the crime detection and prediction techniques along with the superior techniques among them. This study will also present potential challenges and research gaps that will help the researchers and beginners in this area.

B. RESEARCH CONTRIBUTIONS

Numerous contributions have been made in the area of crime hotspot detection and prediction. However, there is a shortage of a comprehensive and systematic literature review that can organize and summarize the significant existing pieces of evidence, potential challenges faced by them, and present the unmet needs. This SLR aims to cover literature from Jan 2010 to December 2019. The primary contributions of this systematic study are to answer the following research questions:

1) RQ1: What empirical evidence of the benefits and limitations of data mining/machine learning approaches currently exist to support the effectiveness of different hotspot detection techniques?
2) RQ2: What data mining/machine learning approaches currently exist to support the effectiveness of different Spatio-temporal hotspot prediction techniques?
3) RQ3: What are the potential challenges highlighted in existing studies to build a robust Spatio-temporal crime prediction model?
4) RQ4: What are the critical characteristics of the datasets used in this study? Do their features seem to affect the results?

The methodology of this SLR is inspired by the guidelines provided by Kitchenham and Charters [25] and weidt and Silva [26]. These guidelines are widely used in literature for conducting SLR [27]–[30]. The SLR is organized as; section II focuses on the state-of-the-art techniques and real world crime prediction approaches, section III discusses the overall methodology, section III-E, and III-F followed the research process guidelines by formulating research questions, study selection, and quality assessment, respectively. Results and discussion are comprehensively presented in section IV, followed by a detailed analysis in section V. The paper concludes with future directions in section VI.

II. RELATED WORK

In this SLR, we searched IEEE, ACM, Springer, Scopus, and Science Direct using the search string ((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)). After an in-depth review, we could not find any SLR during 2010-2019 that focuses on crime hotspot detection and prediction. However, accuracy issues are prevailing in crime hotspot detection, and prediction [31]–[33], and the significance of crime prediction has urged the researchers to contribute to this area. In the following, we first focus on the state-of-the-art techniques, and then real-world crime prediction applications are presented.

Besides, we found 30 significant state-of-the-art studies that discussed the spatio-temporal crime hotspot detection and prediction. Table 1 lists down the surveys, editorial, comparative studies, and mapping studies on a similar area. There are seventeen surveys, two editorials, three comparative studies, and eight mapping studies found during the search process. Out of thirty studies, nine studies focused on crime prediction, nine discussed spatio-temporal crime, six analyze hotspot detection, and six studies enlightened crime mapping significance. The studies are classified into four broad categories based on their focus, including crime prediction, spatio-temporal crime analysis, crime hotspot detection, and crime mapping.

In recent years, machine learning and data mining play an essential role in crime analysis, detection, and prediction. Several studies have been proposed using data mining techniques for solving real-world problems. Predictive mining is one of the most commonly used systematic approaches for predicting such as crime, criminal behaviour, and intrusion detection. Nine studies found that used data mining techniques for crime prediction such as classification, association role mining, ensemble approaches, and classic machine learning techniques [18], [19], [22], [34]–[36], [49]. Yu *et al.* [37] explored the deep learning models such as Recurrent and Convolutional Neural Network for crime prediction due to their promising performance in other fields. They introduced a pipeline to use deep learning models with spatio-temporal data mining techniques. Jiang *et al.* [50] provide a systematic method to use spatial methods for prediction with underlying assumptions, advantages, and disadvantages.

The evolution of GIS and the inclusion of spatial and temporal information led the researchers to propose more robust algorithms for applications such as crime analysis, tracking, dense region specification, and future predictions. Leong and Sung [38] discussed state-of-the-art spatio-temporal crime analysis techniques. They emphasize on the various factor of spatial and temporal data that a crime analyst should consider while analyzing the situation. Again, data mining approaches are considered vital for crime analysis [20], [46], [47], [52]. They discussed predictive policing using analytical and predicting to identify criminals. A few papers used data mining approaches like K-mean, Density-based clustering, and association mining to identify certain patterns for crime such as robbery and suicides. Kapoor *et al.* [23] presented a short survey on crime data using formal concept analysis. Particularly, they focus on crimes in India. Helbich and Leitner [24] published an editorial on the spatio-temporal crime analytics primarily focus on the current trends and unmet needs. Several studies have used spatio-temporal crime analysis for violent crime, residential burglary, and vehicle theft [51], [53].

Recently, spatio-temporal information has been widely used with data mining, and machine learning approaches for crime dense region detection [21], [40], [55]. The proposed studies used data mining techniques to develop new strategies for law enforcement agencies to control crime. Juan *et al.* [39]summarized the spatio-temporal methods that focus on the distribution of crime hotspots and predict its future occurrence. Zeng *et al.* [48] present a comparative study to evaluate the effectiveness of two state-of-the-art spatio-temporal hotspot detection techniques such as scan statistics and risk-adjusted clustering. Deep learning has also been used in crime dense region detection due to its performance and accuracy. Nair and Gopi [54] explored deep learning techniques and found usefull as compared to several data mining techniques.

To visualize, analyze, and track crime or criminal activities, crime mapping is an essential area of research for crime analysts. Crime mapping helps the analyst to identify dense crime regions, trends, and patterns. Data mining techniques have also been used for crime mapping, along with

TABLE 1. Classification of related studies in term of different categories of crime hotspot detection/prevention.

Study	Type	Crime Prediction			Spatio-temporal Crime Analysis			Crime Hotspot Detection			Crime Mapping		
		Technique Analysis	Dataset Analysis	Potential Gaps	Technique Analysis	Dataset Analysis	Potential Gaps	Technique Analysis	Dataset Analysis	Potential Gaps	Technique Analysis	Dataset Analysis	Potential Gaps
[18]	Survey	Supervised	x	x	x	x	x	x	x	x	x	x	x
[19]	Survey	Supervised	✓	x	x	x	x	x	x	x	x	x	x
[20]	Survey	x	x	x	Supervised	x	✓	x	x	x	x	x	x
[21]	Survey	x	x	x	x	x	x	DM/ML^a	✓	x	x	x	x
[22]	Survey	x	x	x	DM	x	x	x	x	x	x	x	x
[23]	Survey	x	x	x	x	✓	✓	x	x	x	x	x	x
[24]	Editorial	x	x	x	x	x	✓	x	x	x	x	x	x
[34]	Survey	x	x	x	DM	x	✓	x	x	x	x	x	x
[35]	Survey	ML/Spatial	x	✓	x	x	x	x	x	x	x	x	x
[36]	Survey	DM	x	✓	x	x	x	x	x	x	x	x	x
[37]	Survey	x	x	x	ML	✓	✓	x	x	x	x	x	x
[38]	Survey	x	x	x	DM	x	✓	x	x	x	x	x	x
[39]	Survey	x	x	x	x	x	x	Spatial	x	✓	x	x	x
[40]	Survey	x	x	Cluster	x	x	x	x	x	x	x	x	x
[41]	Survey	x	x	x	DM	x	x	x	x	x	DM	x	x
[42]	Survey	x	x	x	x	x	x	x	x	x	Web-base	x	✓
[43]	MP^b	x	x	x	x	x	x	x	x	x	Spatial	x	✓
[44]	Survey	x	x	x	Spatial	x	✓	x	x	x	x	x	x
[45]	CS^c	x	x	x	x	x	x	DM	x	x	x	x	x
[46]	CS	x	x	x	x	x	x	DM	x	✓	x	x	x
[47]	CS	x	x	x	Spatial	x	✓	x	x	x	x	x	x
[48]	CS	x	x	x	x	x	x	Spatial	x	✓	x	x	x
[49]	MS	x	x	x	DM/ML	x	✓	x	x	x	x	x	x
[50]	Survey	Supervised	x	x	x	x	x	x	x	x	x	x	x
[51]	MS	x	x	x	x	x	x	Statistical	x	✓	x	x	x
[52]	MS	x	x	x	Regression	x	x	x	x	x	x	x	x
[53]	MS	x	x	x	x	x	x	Supervised	x	✓	x	x	x
[54]	MS	x	x	x	x	x	x	ML	x	✓	x	x	x
[55]	MS	x	x	x	x	x	x	DM	x	✓	x	x	x
[56]	MS	x	x	x	x	x	x	x	x	x	Statistics	x	✓
Proposed	SLR	All Reported	✓	✓	All Reported	✓	✓	All Reported	✓	✓	All Reported	✓	✓

^{a}Data Mining (DM), Machine Learning (ML)
^{b}Mapping Study (MP)
^{c}Comparative Study (CS)

GIS [41], [44], [57]. Zhou et al. [42] present a web-based GIS to map crime hotspots. They proposed a web-based prototype and hypothesized that web-based crime mapping, decision support systems, and reliable internet connectivity could perform well as compare to the traditional system. Mazerolle et al. [56] present the challenges faced by a police department in crime mapping. Ratcliffe [43] discuss the benefits of spatio-temporal crime mapping and different ways to identify dense crime regions.

The scope of existing literature is significant and covers a notable amount of academic research in the spatio-temporal crime hotspot detection and prediction area. However, they are limited in terms of thoroughness, detailed insight, and organization. Our study is the first systematic literature review on spatio-temporal crime hotspot detection and prediction. Primarily, it aims to present recent advancements in crime hotspot detection and prediction. Furthermore, it provides preeminent crime detection and prediction techniques, along with performance measures used in each area. Moreover, this study organizes and summarizes state-of-the-art spatio-temporal crime datasets that are publicly available.

The table 1 classifies the related studies in the broad domain of spatio-temporal crime hotspot detection and prediction into different categories. It is evident from the table that the proposed study covers almost all essential aspects of spatio-temporal crime hotspot detection and prediction. Furthermore, the potential challenges faced by state-of-the-art studies are highlighted and future research directions are discussed.

III. RESEARCH METHOD

A wide range of literature has been reported for crime hotspot detection and prediction. The primary objective is to investigate which methods are superior as compared to others in Spatio-temporal crime hotspot identification and predicting. One crucial point is to study the impact of Spatio-temporal datasets as compared to other datasets presented in the literature for crime hotspot identification and predicting. The other important thing in this SLR is to present potential challenges faced by the proposed techniques in literature that can make a crime identification and predicting algorithm more robust. To the best of the author's knowledge, this SLR

on crime hotspot detection and prediction is a first attempt from 2010-2019.

This SLR is performed using the guidelines provided by [25]. It is stated in the instruction that; an SLR defined as planning, evaluation, and reporting the available research relevant to a particular research area, question, topic, or field of interest. The motivation for performing such a review is to identify the existing approaches regarding the use of a particular technology, to determine the potential challenges and gaps in the current research and a direction for properly conducting new research in this direction [26]. Almost all the literature on SLR suggests that it consists of three stages: planning, conducting, and reporting the review. Kitchenham and Charters [25] proposed a more refined form of these steps as follows:

1) Define the research questions.
2) Identify a few relevant studies and perform a pilot study.
3) Search data on the relevant databases (IEEE, Springer, ACM, Science Direct).
4) Document the search strategy
5) Appraisal and selection of studies.
6) Analyzing and presenting the results.
7) Discuss the generalized conclusion and limitations of the review.
8) Make recommendations

The overall objective of the planned SLR is to analyze and summarize the results to date on Spatio-temporal hotspot identification and prediction and to find the potential gap and opportunities for future research directions in this area.

A. RESEARCH QUESTIONS

It is essential to find the right research questions to interpret the state-of-the-art Spatio-temporal crime hotspot identification and predicting empiric research. The primary motivation behind this SLR is to identify the current tendency and factors that can impact the identification and prediction of crime hotspots. The research questions are structured and prepared based on the [25] criteria population, intervention, outcome, and context (PIOC).

In context with the criteria mentioned in Table 2 following research questions need to be addressed in this SLR:

TABLE 2. Criteria for research questions.

Population	Crime prediction technique and applications
Intervention	Techniques/Methods for Spatio-temporal crime hotspot identification and prediction
Precision	Accuracy of crime hotspot identification and predicting techniques, efficient and effective crime hotspot identification and predicting techniques
Context	Confines academia and Crime investigation approaches. All empirical pieces of evidence, observations, case studies, and frameworks

1) RQ1: What empirical evidence of the benefits and limitations of data mining/machine learning approaches currently exist to support the effectiveness of different hotspot detection techniques?
   a) RQ1a: What techniques have been reported for the detection of Crime Hotspots?
   b) RQ1b: What detection approaches are reported to be superior for crime hotspot detection based on empirical evidence?
   c) RQ1c: What performance measures have been taken for measuring the accuracy of detection of Crime Hotspots?
2) RQ2: What data mining/machine learning approaches currently exist to support the effectiveness of different Spatio-temporal hotspot prediction techniques?
   a) RQ2a: What techniques have been reported for the Prediction of Spatio-temporal Crime Hotspots?
   b) RQ2b: What Spatio-temporal prediction approaches are reported to be superior for crime hotspot detection based on empirical evidence?
   c) RQ2c: What performance measures have been taken for measuring the accuracy of Spatio-temporal prediction of Crime Hotspots?
3) RQ3: What are the potential challenges highlighted in existing studies to build a robust Spatio-temporal crime prediction model?
4) RQ4: What are the critical characteristics of the datasets used in this study? Do their features seem to affect the results?
   a) RQ4a: Which type of dataset has been used for this research (Professional or self-acquired)?
   b) RQ4b: What are the main aspects of a dataset for the Spatio-temporal crime hotspot? Do they affect results?

Usually, the SLR's presented in literature follow planning, evaluating, and reporting as significant steps which itself consists of several substeps. In this SLR, the aim is to follow the mechanism provided by [25], and they proposed to start SLR with a pilot study to check the feasibility and appropriateness of research questions and to explore the viability of gathering and analyzing the data to answer the proposed research questions. We followed the process by an initial pilot study on a set of papers to check the appropriateness of proposed research questions. Did the included articles have essential data to answer the research questions and the feasibility of the proposed analysis? Based on this insight, the plan was polished, and a full through SLR on the Spatio-temporal crime hotspot identification and predicting is performed.

B. SEARCH STRATEGY

A well-planned search strategy is fundamental in an SLR to extract relevant research work from the search results. Therefore, a substantial search for the research paper was conducted to answer the proposed research questions. We used

the steps recommended by [58] to prepare the search terms used in this SLR:

1) Derive significant search terms from the research questions by identifying population, intervention, outcome, and context.
2) Enlist the keywords in the relevant papers.
3) Point out alternative spellings and synonyms for search terms with the help of a dictionary.
4) Use Boolean AND to concatenate the search keywords for confined research.
5) Use OR to construct search keyword from search terms with similar meanings.

C. SEARCH STRING

The resultant search strings are as follows:

SPATIO: ''Spatial''**OR** ''Dimensional'' **OR** ''Geographical'' **OR** ''Contiguous'' **OR** ''Structural'' **AND**
TEMPORAL: ''Earthly'' **OR** ''Materialistic'' **OR** ''Physical'' **OR** ''Sensual'' **AND**
CRIME: ''Atrocity'' **OR** ''Breach'' **OR** ''Case'' **OR** ''Corruption'' **OR** ''Evil'' **OR** ''Felony'' **OR** ''Infraction'' **OR** ''Lawlessness'' **OR** ''Misconduct'' **OR** ''Misdeed'' **OR** ''Scandal'' **OR** ''Violation'' **OR** ''Wrongdoing'' **AND**
HOTSPOT: ''Intense'' **OR** ''Dense'' **AND**
DETECTION: ''Observation'' **OR** ''Noticing'' **OR** ''Identification'' **OR** ''Spotting'' **OR** ''Recognition'' **OR** ''Diagnosis'' **OR** ''Sensing'' **AND**
PREDICTION: ''Forecasting'' **OR** ''Prophecy'' **OR** '' Divination'' **OR** ''Augury'' **OR** ''Projection'' **OR** ''Prognosis'' **OR** ''Guess''

These search strings are included to find relevant papers from the literature. Some terms are confusing, as shown in Table 3 but we added them to maximize the consistent search outcome. However, the studies will be excluded from the study selection stage if it is not related to crime hotspot detection and prediction.

TABLE 3. Keyword synonyms.

Keyword	Synonyms
Spatio	Spatial, Dimensional, Geographical, Contiguous, Structural
Temporal	Earthly, Materialistic, Physical, Sensual
Crime	Atrocity, Breach, Case, Corruption, Evil, Felony, Infraction, Lawlessness, Misconduct, Misdeed, Scandal, Violation, Wrongdoing
Hotspot	Intense, Dense
Detection	Observation, Noticing, Identification, Spotting, Recognition, Diagnosis, Sensing
Prediction	Forecasting, Prophecy, Divination, Augury, Projection, Prognosis, Guess

The search strategy comprised of the following decisions:
We used a custom range of Publication period from 2010 to December 2019 as that is the time literature performed. Hence any paper published after December 2019 is not included in this study, as shown in Table 4.

TABLE 4. Search strategy decisions.

Searched Databases	IEEE Xplore [59],Springer Link [60], ACM digital library [61], Science Direct [62], Scopus [63]
Searched Items	Journal papers, conference papers, workshops, and magazines
Search Applied On	Full-text papers: Aim is to avoid exclusion of those papers that do not have the keywords in their title or abstract, but they are still relevant for literature review.
Publication Period	Since Jan, 2010

D. STRING REFINEMENT

Once the string is formed, it is crucial to validate the search results returned from defined search engines. Potential papers for primary study should appear in the result. If no known paper appears, or very few returned, the search string must be calibrated. To refine the search string, we must have to refine our synonyms identified as well as the search criteria in each search engine.

We have to check the effect of inclusion and exclusion of synonyms, publication type, year limit, language, research area, and specific journals, etc., on individual bases until satisfied with the results. The search string evolution process for this SLR is shown in Fig. 2. Table 5 shows the paper returned after various limits applied with the final search string to the searched databases.

TABLE 5. Search limits on searched databases.

Databases	Limits	Returned Papers
IEEE	2010-2019, English, Conferences, Journals, Magazines, workshops	13
Springer	2010-2019, English, Conferences, Journals, Magazines, workshops,CS, Data Mining and Knowledge Discovery	99
ACM	2010-2019, English, Conferences, Journals, Magazines, Workshops, Publication Title (Applied geography, Political geography, Cities, Computer, Environment and urban system)	120
Science Direct	2010-2019, English, Article and Conferences, Journals, Magazines, Workshops, Computer science, Keywords (Crime, forecasting, data mining, Learning system)	124
Scopus	2010-2019, English, Article and Conferences, Journals, Magazines, workshops, Applied Geography	19
Total		375

There are certain limits individually applied, and some limits are commonly applied to a search engine like; English Language, year (2010-2019), article type (conference, journal, magazine, and workshop). IEEE Explorer returned very
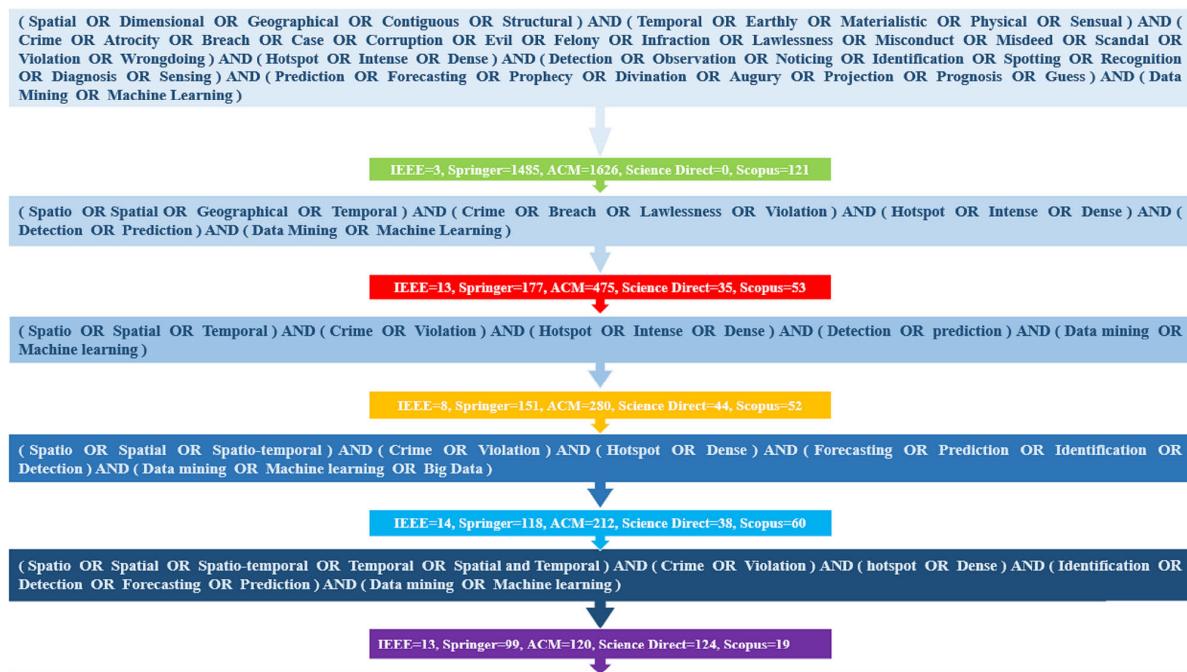
(Spatial OR Dimensional OR Geographical OR Contiguous OR Structural) AND (Temporal OR Earthly OR Materialistic OR Physical OR Sensual) AND (Crime OR Atrocity OR Breach OR Case OR Corruption OR Evil OR Felony OR Infraction OR Lawlessness OR Misconduct OR Misdeed OR Scandal OR Violation OR Wrongdoing) AND (Hotspot OR Intense OR Dense) AND (Detection OR Observation OR Noticing OR Identification OR Spotting OR Recognition OR Diagnosis OR Sensing) AND (Prediction OR Forecasting OR Prophecy OR Divination OR Augury OR Projection OR Prognosis OR Guess) AND (Data Mining OR Machine Learning)

IEEE=3, Springer=1485, ACM=1626, Science Direct=0, Scopus=121

(Spatio OR Spatial OR Geographical OR Temporal) AND (Crime OR Breach OR Lawlessness OR Violation) AND (Hotspot OR Intense OR Dense) AND (Detection OR Prediction) AND (Data Mining OR Machine Learning)

IEEE=13, Springer=177, ACM=475, Science Direct=35, Scopus=53

(Spatio OR Spatial OR Temporal) AND (Crime OR Violation) AND (Hotspot OR Intense OR Dense) AND (Detection OR prediction) AND (Data mining OR Machine learning)

IEEE=8, Springer=151, ACM=280, Science Direct=44, Scopus=52

(Spatio OR Spatial OR Spatio-temporal) AND (Crime OR Violation) AND (Hotspot OR Dense) AND (Forecasting OR Prediction OR Identification OR Detection) AND (Data mining OR Machine learning OR Big Data)

IEEE=14, Springer=118, ACM=212, Science Direct=38, Scopus=60

(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)

IEEE=13, Springer=99, ACM=120, Science Direct=124, Scopus=19

FIGURE 2. Search query evolution process.

few results as compared to other search databases throughout the query evolution process. For Springer, we further limit the search by selecting journal names (Data mining and Knowledge Discovery) from suggested journals, which results in fine-tuned papers. ACM results improved a lot after limiting content type PDF with all the conventional limits. Science Direct has a specific limitation that search does not support more than 8 Boolean connectors per field; therefore, we could not find any papers. Later, we calibrated the search with the addition of journal name (Applied Geography) and publication title. Lastly, the Scopus search engine is used with articles, and conference papers limit resulted in 19 papers. The resultant final paper distribution in every search engine is shown in Fig.4.

E. STUDY SELECTION

The composed search strategy resulted in 375 candidate papers, as shown in Fig. 5. We excluded the research papers based on three widely used selection criteria: Title and Abstract based Analysis, Introduction and Conclusion Based Analysis, and Full paper and Quality Assessment based analysis. In the first phase, 124 papers were excluded based on title and abstract analysis. Leftover, 251 papers further analyzed by reading the introduction and conclusion part of the paper. During the second phase, 107 papers were eliminated from the candidate papers. Remaining 144 papers examined in the final phase, based on full text, quality assessment criteria, and by critically evaluating the significance of work, 95 papers were excluded, and 49 papers left as candidate papers for this SLR. The frequency distribution of papers selected over the years is shown in Fig.3.
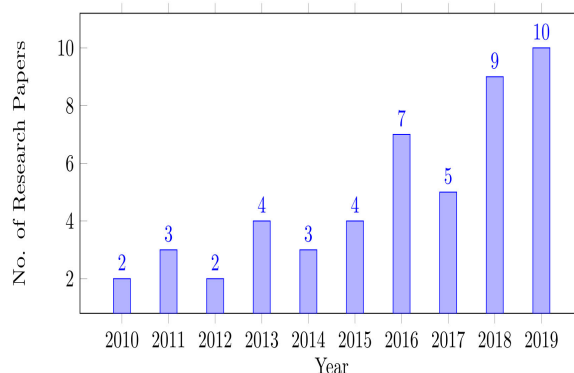
FIGURE 3. Year wise distribution of selected studies.

1) INCLUSION CRITERIA

1) The study focus on the detection of crime hotspot
2) The study focus on the prediction of crime hotspot
3) Current practices for crime prediction by law and enforcement agencies
4) Among duplicate publications of the same study, the most thoroughgoing and recent included.

2) EXCLUSION CRITERIA

1) Secondary studies (e.g. systematic literature, survey)
2) Studies that are written in a language other than English
3) Studies that have not been peer reviewed
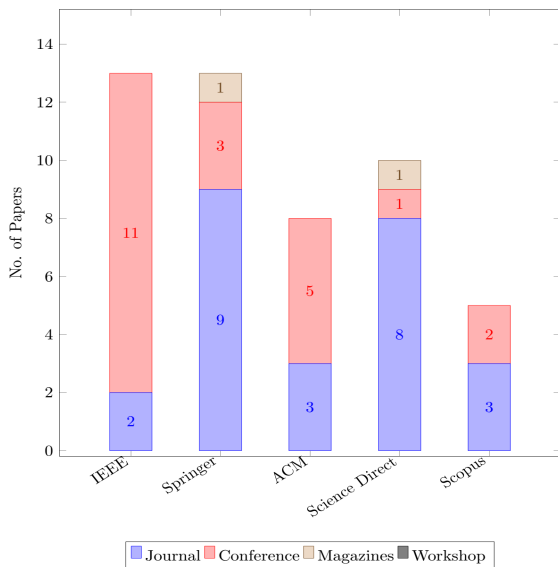4) Studies that are not available in full-text
5) Later than Jan, 2010

FIGURE 4. Article type distribution in searched databases.

FIGURE 5. Summary of search process.

FIGURE 6. A way of organizing SLR data in a Table for better understanding.

To answer the research questions, all the studies that identified in this SLR, read comprehensively, and thoroughly to produce the data needed to answer. It would be appropriate to organize all the extracted information in a Table that originated from the SLR. The assembled data can then highlighted in different colors according to various research questions, as shown in Fig. 6. This technique will help the researcher to keep track, detect, and validate the required information timely.

F. QUALITY ASSESSMENT

In this SLR, a checklist of quality assessment (QA) is customized for the evaluation of individual studies based on guidelines provided by [26] and [25]. In the literature, several studies [64], [65], and [66] have customized the quality assessment criteria based on the guidelines provided in [25]. We used a three-point scale method for the Quality assessment checklist, as shown in Table 6. If the point is present (P), it will add one to the score; in case of absence (A), it will be zero, and if the study is sufficient (S), it will be 0.5. There is a maximum of 12 points a study can achieve based on the number of QA questions. We chose the first quartile $(12/3 = 4)$ as an inclusion number for this SLR. If an investigation cannot score higher than 4, it would be discarded, as shown in Table 7.

1) THREATS TO VALIDITY

This SLR may suffer from validity threats. We should consider these threats while analyzing and reporting our findings. We have excluded the paper from our prime study that does not have a spatial-temporal and crime hotspot in their titles. So, we may have overlooked several studies that are associated with Spatial-temporal crime prediction, but they have not mentioned these terms in the title.
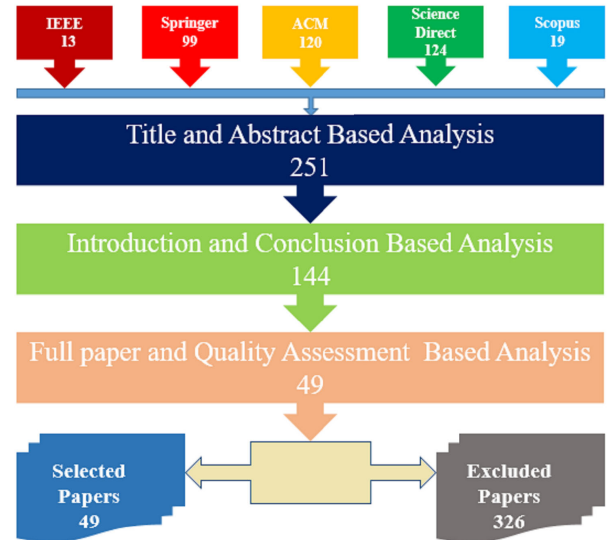
TABLE 6. Customized quality assessment criteria adopted from [25], [64].

Sr.	Questions	Points
1.	Are the study objectives clearly defined?	P/A/S
2.	Techniques/Methods for Spatio-temporal crime hotspot identification and prediction Was the study planned to accomplish the objectives?	P/A/S
3.	Are the identification and prediction techniques described clearly?	P/A/S
4.	Do the study measure the features suitable?	P/A/S
5.	Are the data collection methods reported clearly?	P/A/S
6.	Is the collected data presented in-depth?	P/A/S
7.	Is the motivation behind data analysis coherent?	P/A/S
8.	Do the statistical analysis techniques adequately describe the data?	P/A/S
9.	Are potential challenges presented in the study?	P/A/S
10.	Do the researchers identify issues in their study?	P/A/S
11.	Can research questions be answered from this study?	P/A/S
12.	Do the experimental work aligned with the conclusion and compared it with State-of-the-art?	P/A/S

Studies are also excluded due to the lack of scientific thoroughness. A substantial number of literature reported by new beginners in academia and industry may lie in this category. It was analyzed during the pilot study, and while defining inclusion and exclusion criteria that comparison with

TABLE 7. Quality assessment criteria of scoring the papers.

Study	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	QA9	QA10	QA11	QA12	Points (P/A/S)
[67]	S	S	A	S	A	A	A	S	S	P	S	A	4
[68]	P	S	S	S	S	A	A	A	A	S	S	A	4
[69]	P	P	P	P	S	A	S	S	P	P	P	P	9.5
[50]	S	P	S	S	A	S	A	A	A	A	P	S	4.5
[70]	P	P	P	S	A	S	A	S	A	S	P	P	7
[71]	P	P	S	S	A	A	A	A	A	P	S	S	5
[72]	S	S	A	S	S	A	A	P	A	S	S	A	4
[73]	P	P	S	S	A	S	A	S	A	S	S	S	5.5
[74]	S	S	S	A	A	A	S	S	S	P	S	A	4.5
[75]	P	S	S	S	A	A	A	A	S	S	P	S	5
[76]	P	P	P	P	S	S	P	P	S	S	P	P	10
[77]	S	S	S	S	A	A	A	P	S	A	S	A	4
[78]	P	S	S	S	A	A	A	S	S	A	S	S	4.5
[79]	P	P	P	S	S	A	A	S	P	P	S	P	8
[80]	P	P	S	S	A	A	A	A	A	S	A	S	4
[81]	S	S	S	P	S	A	A	A	S	P	S	S	5.5
[82]	P	P	S	S	A	S	A	A	A	S	S	P	5.5
[83]	S	S	S	A	A	A	A	A	P	P	S	A	4
[84]	P	P	S	S	A	A	A	A	S	S	S	S	5
[85]	S	S	P	A	A	A	P	S	P	P	S	P	7
[86]	P	S	P	S	S	S	A	A	A	P	S	S	6
[87]	P	P	P	P	P	S	S	A	A	S	P	P	8.5
[88]	P	S	S	A	A	A	S	S	A	A	S	S	4
[89]	S	S	A	A	S	S	A	A	A	P	P	S	4.5
[90]	P	P	A	A	A	S	A	S	S	S	S	A	4.5
[91]	P	S	A	A	S	P	S	S	A	P	S	P	6.5
[92]	S	S	S	A	A	S	A	A	A	P	P	S	4.5
[93]	P	P	S	A	A	S	S	A	P	P	S	P	7
[94]	P	A	A	P	S	S	S	S	A	A	S	S	5
[95]	P	S	S	S	A	A	A	P	S	A	S	S	5
[96]	P	P	P	P	S	S	A	S	S	P	S	P	8.5
[17]	P	S	S	S	A	A	S	A	P	S	S	P	6
[97]	P	A	S	A	S	A	A	S	S	A	P	P	5
[98]	P	P	A	A	A	A	S	A	P	P	P	S	6
[99]	S	A	A	A	A	A	S	S	P	S	S	S	4
[100]	P	S	S	P	A	A	S	S	A	S	S	A	5
[101]	P	P	P	P	A	A	A	S	S	S	P	S	7
[9]	S	A	A	A	S	S	A	P	P	A	S	S	4.5
[102]	P	A	A	A	A	A	P	P	A	S	S	A	4
[103]	S	A	A	P	S	A	A	P	P	A	S	S	5
[104]	S	P	A	A	S	A	S	A	A	P	S	A	4
[105]	P	P	P	P	P	P	P	S	P	A	P	S	10
[106]	S	S	A	A	A	A	P	P	S	A	S	A	4
[107]	P	P	P	A	A	A	P	S	P	P	P	S	8
[108]	P	P	A	A	A	A	S	P	S	A	A	S	4.5
[109]	P	A	A	P	A	A	P	S	A	A	A	S	4
[110]	P	A	A	P	A	A	P	S	A	A	A	S	4
[16]	P	P	A	A	A	P	A	P	A	A	A	P	5
[111]	P	S	A	A	A	A	P	P	A	A	P	A	4.5

the state-of-the-art is missing in all aspects. It is beneficial to collate with the research and academia to make a substantial scientific contribution.

One primary concern in research is to explore publicly available datasets. A detailed description and origin of the majority of the crime dataset are found missing in the literature due to its sensitivity. These datasets may be referred to as "grey literature" such as a scientific report. So this may result in a dissatisfaction that SLR fails to cite such valuable datasets and their scientific contribution.

2) VALIDATION OF SYSTEMATIC LITERATURE REVIEW

The validation of this SLR is performed by following the guidelines provided by Kitchenham and Charters [25]. Only a couple of studies duly follow all the SLR steps. The only articles are considered where the mutual consensus is reached by both the researchers by following an inclusion/exclusion criteria. The rest of the researchers mainly contributed to the planning and development protocol, working primarily as supervisors. Moreover, the validation involves fine-tuning of the search query and searches query process, and the priority is given to the most cited literature.

The query refinement process is crucial to ensure that the returned papers are relevant and aligned with the defined research questions. The search query refinement process is shown in Fig. 2 and calibrations are performed until the required literature is returned. It was revealed during the study selection process that some studies are duplicated; they were first included in the conference proceedings [105] and then were published by a journal as extended versions [112]. Furthermore, quality assessment criteria III-F are defined by following the guidelines provided in [25], [26].

IV. RESULT AND DISCUSSION

The result and findings are presented in this section extracted from the reviewed papers to answer the research questions. All the research questions are answered according to the relevant studies highlighted during the SLR.

A. SPATIO-TEMPORAL CRIME HOTSPOT DETECTION TECHNIQUES (RQ1a)

There are 11 techniques extracted from the studies reported for Spatio-temporal crime hotspot detection. These are as follows:

- PCA
- GD Patterns
- TCP
- FP-Growth
- LIBSVM
- CCRBoost
- MLP
- Random Forest, Naïve Bayes, J48, Decision Tree
- SANET+Kernel Density Function
- Fuzzy C-Mean
- DBSCAN

In this review, we classified the ensemble-based approach Random forest and Naïve Bayes, J48, and decision trees in the same category. Random forest normally operates on constructing decision trees and can be used for classification. The trending deep learning-based methods have also been used for hotspot detection and are comparable in performance with traditional state-of-the-art classification techniques. Classification techniques used less as compared to clustering, as shown in Fig. 7, along with the ensemble approaches for hotspot detection. Clustering approaches are also extensively used in the literature from the past few years, as shown in Table 8.

Clustering approaches are comparable in performance with the classification and ensemble approaches. From the last few years with the increasing usage of Spatio-temporal information in datasets clustering approaches performs relatively well in hotspot detection. Specifically, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is a density-based unsupervised clustering approach that has been reported recently with comparable performance in hotspot detection [105].
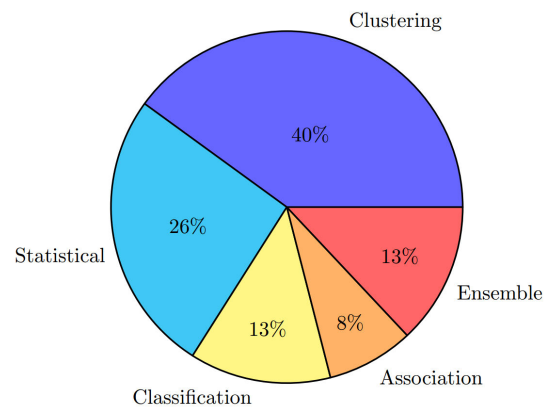

FIGURE 7. (%) Distribution of crime hotspot detection approaches.

1) SUPERIOR SPATIO-TEMPORAL CRIME HOTSPOT DETECTION APPROACHES (RQ1B)

The primary objective of this SLR is to provide ease for beginners who want to contribute to Spatio-temporal crime prediction. Most researchers and beginners would like to know the most prominent techniques that have been reported so far for crime hotspot detection. In this section, we discuss some outstanding approaches so far reported; however, it is difficult to answer precisely because every study has its context of hotspot detection.

A few superior and prominent techniques for Spatio-temporal crime hotspot detection have been identified in the literature in terms of the best technique of paper, suggestions, and future work. The preeminent techniques that are compared with state-of-the-art in a particular study are shown in Table 9. As mentioned earlier, some researchers have mentioned the best technique among the ones they implemented and compared. However, they are according to the dataset being used, performance measures being used, and in a particular scope.

In this SLR, during the pilot study and after a thorough review of literature shortlisted, mixed results are identified as they are in a particular setting, which is different in others. The majority of the literature does not have a dataset description and not even any link to access and compare results, so it is hard to conclude the prominent approaches they have mentioned. A few papers use [5], [71], [105], [112] same publically available crime data and compare their results in a particular setting. However, researchers such as Kadar *et al.* [104] and Rumi [100] use different datasets to check the effectiveness of their proposed approach.

Catlett *et al.* [105] discuss the potential challenges faced by the researchers in obtaining crime data from the criminal investigation department of different countries. There are few studies recently reported that uses spatial and temporal information from the datasets for crime prediction. The majority of reported datasets do not have space and time information, so it is challenging to compare techniques based on this fact that crime detection approaches improve a lot

TABLE 8. Spatio-temporal crime hotspot detection techniques.

Reference	Techniques	Data	Results/Description
[86]	Hot Spots prediction model based on mixed spatial-temporal characteristics	Data of Main city zone of Nanchang ranging from 2014 to 2015	Optimal performance can be achieved by the prediction model if crime statistics are conducted on weekly basis
[91]	STNN Decision Tree Gaussian Naive Bayes Random Forests K-nearest neighbors Logistic Regression Multi-layer perception	Call-for-service data provided by the Portland, Oregon Police Bureau (PPB) for a 5-year period from March 2012 through the end of December 2016	81.50% Accuracy 76.00% Accuracy 74.30% Accuracy 76.25% Accuracy 63.75% Accuracy 75.00% Accuracy 76.75% Accuracy
[92]	Random Forests	Data of 12 years, 2003 to 2015, San Francisco (US), of crime records and on one from Natal (Brazil) with 10 years (2006-2016) of crime records	Features such as street network contains important information regarding crime based activities
[93]	Kernel Density Estimation (KDE)	Crimes occurred in Manila, Philippines from the year 2012 to 2016	Criminal activities in Manila are at peak around 8:00 PM to 4:00 AM
[98]	spatio-temporal kernel density estimation (STKDE)	Data of residential burglaries in Baton Rouge, Louisiana in 2011	Southwest area of Baton Rogue is identified as the high-risk area
[113]	Hierarchical Density-Based Spatial Clustering of Applications with Noise	Crime data from Royal Canadian Mounted Police of Halifax, NS	A significant performance improvement was observed in hot-spot detection using proposed methodology
[101]	Spatio-temporal Ordinary Kriging	Crime dataset of Philadelphia from January 2011 to December 2016	90.52% Sensitivity
[112]	DBSCAN	Crimes Dataset of New York city and Chicago	Hot-spot detection

after the usage of Spatio-temporal information. Spatial and temporal information addition in datasets found to be more effective for crime prediction. Catlett *et al.* [112] pointed out the DBSCAN approach to be superior among all the crime detection approaches as they compared with state-of-the-art techniques. They used publically available Chicago crime dataset that is used in many crime hotspot detection papers. They also suggested using a hierarchal clustering algorithm instead of DBSCAN.

The detailed comparison of crime hotspot techniques is presented in Table 9. It can be seen from the Table that clustering approaches are most widely used in the literature. Among them, DBSCAN found to be more reliable and effective as compared to state-of-the-art techniques. Apart from that, classification and ensemble approach MLP, Naïve Bayes, SVM, and Random Forest are also reported in higher numbers and found to be useful. Among them, Random Forest is quite effective mentioned by a few papers.

With the increasing usage of spatial and temporal information, clustering becomes more effective, as shown in the Table 9. Catlett *et al.* [105] use DBSCAN to predict crime hotspot and evaluate on a publically available Chicago crime dataset. DBSCAN found to be outstanding as compared to other state-of-the-art approaches. The primary reason behind their work is that they evaluate their proposed approach in Chicago as well as other datasets that are also commonly used in the past. However, they also discuss the shortcomings of DBSCAN and suggest to use hierarchical clustering instead. So still a research gap exists that needs to be addressed in the future.

TABLE 9. Superior crime hotspot detection techniques.

Study	Techniques Compared	Preeminent Technique
Zhanhong et al. [69]	PCA	PCA
Dawaiet et al. [114]	HOT-GD patterns	HOT-GD patterns
Omowonmi et al. [73]	FP-Growth	FP-Growth
Faian et al. [85]	Stanford NER vs Baseline vs LibSVM	LibSVM
Chung et al. [87]	C4.5 vs Naïve Bayes vs SVM vs Random Forest vs CCRBoost	CCRBoost
Julio et al. [92]	MLP vs Random Forest	Random Forest
Maria et al. [93]	Bayes Net vs J48 vs Random Forest	Random Forest
Shoaib et al. [115]	Network Kernel Density Estimation (NetKDE)	Network Kernel Density Estimation (NetKDE)
Ferdinando et al. [96]	Fuzzy C-mean vs ST-DBSCAN	Fuzzy C-Mean, DBSCAN
Charlie et al. [112]	DBSCAN	DBSCAN

2) PERFORMANCE MEASURES FOR SPATIO-TEMPORAL CRIME HOTSPOT DETECTION TECHNIQUES (RQ1C)

Several methods have been used in the literature to evaluate the performance of a Spatio-temporal crime hotspot detection

technique. As, various approaches have been reported to detect the dense crime regions such as; Clustering, Classification, Frequent pattern mining, Ensemble, Deep Learning, etc. Therefore, different performance measures have been chosen based on the approach. It is vital to gather all the information about the performance measure that is widely used and found to be effective.

During the SLR study, it was found that Accuracy, Root Mean Square Error (RMSE), and F1_score are commonly used in the literature for various approaches. For frequent pattern mining, min-support and confidence measures are reported frequently. Apart from that, standard deviation, Variance, mean, and correlation measures have also been used.

From Table 10, it is evident that the accuracy measure is used in 45% of the studies. Support and confidence measure is used in numerous pattern matching techniques and reported around 20% of the studies. ROC curve, F1_score, and Kappa Index Measure have also been reported. So, from the above examination, it is concluded that Accuracy measures, especially sensitivity and specificity, are commonly used in literature for different evaluation kinds of crime hotspot detection techniques; however, some performance measures are specific for a particular approach like Support and confidence.

TABLE 10. Evaluation measures reported for crime hotspot detection.

Study	Techniques Compared	Preeminent Technique
Zhanhong et al. [69]	PCA	Z-score, Variance
Dawaiet et al. [114]	HOT-GD patterns	Kappa Index
Omowonmi et al. [73]	FP-Growth	Min_Support, Confidence
Faian et al. [85]	LibSVM	Accuracy
Chung et al. [87]	CCRBoost	Accuracy, F1_Score
Julio et al. [92]	Random Forest	ROC Curve, Accuracy, F1_Score
Maria et al. [93]	Random Forest	ROC Curve, Accuracy
Shoaib et al. [115]	Network Kernel Density Estimation (NetKDE)	Kappa Index
Ferdinando et al. [96]	Fuzzy C-mean, ST-DBSCAN	Accuracy, RMSE
Charlie et al. [112]	DBSCAN	Accuracy, RMSE

B. SPATIO-TEMPORAL CRIME PREDICTION TECHNIQUES (RQ2A)

Several techniques have been reported for Spatio-temporal crime forecasting. For this SLR, we have classified them into six different categories: Deep learning-based, Classical Classification approaches, Statistical, Time series analysis, Regression Techniques, and clustering techniques. Classification approaches are reported in the majority, around 50% of

total approaches, as shown in Fig. 8. We further divided them into classical and deep learning-based, as shown in Table 11.
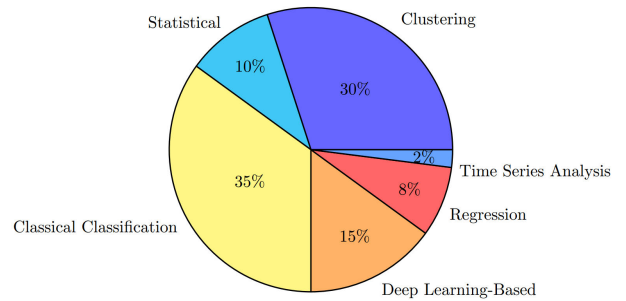
FIGURE 8. (%) Distribution crime prediction approaches.

- MLP, NN, GA-BP Neural Network, DNN, CNN, Spatio-temporal Neural Network
- Random Forest, Naïve Bayes, J48, Decision Tree, K-NN, Classification and Regression tree, SVM, LIBSVM, M5P
- SANET+Kernel Density Function, Temporal Correlation prediction framework, GD Patterns-Hotspot Optimization Tool, Spatio-temporal Generalized Additive Model, Spatio-temporal Ordinary Kriging
- ARIMA
- Ridge Regression, Lasso Regression
- Fuzzy C-Mean, DBSCAN, Clustered CCRF, Cluster Confidence Rate Boosting (CCRF), K-mean

Researchers attempted different kinds of approaches like regression approaches and some Spatio-temporal models based on statistics. They are around 12% of the total approaches. Among all, Clustering approaches have also been reported extensively and found to be useful as compare to classification approaches, particularly DBSCAN and Fuzzy C-Mean are reported recently with the comparable performance [96].

In 2017, the United States Department of the national institute of justice hosted a real-time crime forecasting challenge to address the challenges of crime and criminal justice [126]. This competition aimed to develop crime prediction algorithms to improve knowledge, understanding of crime, and to reduce crime before it takes place. The challenges consist of three categories, students, small businesses, and large businesses. Four crime types are addressed, such as residential burglary, commercial burglary, street crime, and vehicle theft. Portland police bureau provided the Call-For-Service (CFS) data of their jurisdiction from March 2012 to February 2017. Sixty-two algorithms were submitted by the data scientist. Top 4 contestants were students, 19 were from small business units and ten algorithms from the large business. Mohler *et al.* [120] Mohler and Porter [127] proposed a novel method that selects an optimal grid size, orientation, and a scoring function that maximizes the Predictive Accuracy Index (PAI). Lee *et al.* [121] use population heterogeneity theory to find areas of consistent crime and state dependency theory to address short term risk in certain places.

TABLE 11. Spatio-temporal crime prediction techniques.

Reference	Techniques	Data	Results/Description
[116]	Cluster-Confidence-Rate-Boosting (CCRBoost)	Ranging from January 2006 to December 2009, From a Police department in a city from northeastern, US	80% Accuracy
[86]	LDA-KNN	Ranging from 2014 and 2015, data of main city zone of Nanchang	The algorithm manifests commendable prediction performance, either around holidays or at ordinary times
[88]	GA-BP neural network model	Crimes that occurred from 2008 to 2012, at city in South China	The accuracy results is based on the accuracy of input data
[117]	Negative binomial regression	Large-scale Point-Of-Interest and taxi flow data in Chicago, US	Infer crime rates in different city areas, integrating geographic, demographic, POIs and taxi flows data
[90]	TCP	From July 1, 2012 to June 30, 2013 in New York City	The results retrieved by the experiments on data shows the effectiveness of the framework
[118]	Traditional Regression Methodologies	Public dataset of crime occurrences reported from March 2012 to December 2016 in Portland, Oregon	Results demonstrates that regressions outperforms a window averaging method
[119]	Spatial point pattern test	Vancouver Dataset of crimes 2003-2013	Investigate the spatial concentrations and spatial stability
[91]	Recurrent neural networks model	Call-for-service data provided by the Portland, Oregon Police Bureau (PPB) from March 2012 to December 2016	Exploits spatial and temporal information for forecasting crime hotspots
[13]	Deep learning using ST-ResNet	Crime Dataset of Los Angeles	Prediction of hourly crime rates
[93]	BayesNet Naive Bayes J48 Random Forest Decision Stump	Gun shooting crimes incurred from the year 2012 to 2016 in Manila, Philippines	77.41% Accuracy 77.78% Accuracy 73.84% Accuracy 76.34% Accuracy 77.06% Accuracy
[120]	Random Forest and Logistic Regression	CFS data of Portland	84.99% PAI
[121]	Population heterogeneity and State dependency theory	CFS data of Portland	72-74 % Accuracy
[122]	Localized kernel density function and Evolutionary algorithms	CFS data of Portland	LKDE and KDE achieved good accuracy
[123]	Probability density function and Kernal smoothing	CFS data of Portland	PAI 2.77
[124]	Geospatial software (OpenJump)	CFS data of Portland	NA
[5]	(Clustered-CCRF)	Crime records in Chicago from online platform from January 1 2013 to January 1 2016	3.1382 RMSE
[17]	Autoregressive Integrated Moving Average model (ARIMA)	Daily police data provided by the Public Security Bureau (PSB) of a city in China	Prediction results meet the expected requirements and are more accurate
[125]	Cluster Confidence Rate Boosting algorithm	Five publicly available datasets composed of police reports	Prediction of residential burglary using DSTP and ESTP
[100]	Random Forest, Neural Network, SVM, Logistic Regression Model	The crime event records of Queensland, Australia from 01/2013 to 09/2013 and New York City from March, 2012 to February, 2013	With the inclusion of dynamic features across diverse types of criminal events, crime prediction performance can be significantly improved
[99]	Random Forest	Crimes dataset provided by Department of Informatics of the Brazilian Public Health System	97% accuracy
[112]	ARIMA	Crimes Dataset of New York city and Chicago	Crime forecasting

Al Boni and Gerber [122] proposed a novel method for hotspot analysis with a hybrid of the localized kernel density function and evolutionary algorithms. They also explore the effect of data sparsity on the performance of these models. Koontz [123] use Probability Density Function (PDF) with kernel smoothing function to measure the PDF of historical data and use these probabilities to forecast the crime area. Ledray *et al.* [124] used open-source geospatial software (OpenJump) for past data crime mapping and used the C library to mark

hotspots. After that, they used data mining approaches for forecasting.

Recently, Time series analysis techniques have been introduced for crime forecasting [105] as clustering and classification approaches fail to provide promising results in this area. These challenges are addressed by introducing Time series analysis techniques called Auto Regressive Moving Average (ARMA) techniques in crime forecasting. A generalized model of ARMA called Auto Regressive Integrated Moving Averages (ARIMA) has been reported recently and outperformed as compared to state-of-the-art techniques [112]. It has been found that ARIMA models have some shortcoming which needs to be addressed and a research gap still exist in this area for future researchers.

1) SUPERIOR SPATIO-TEMPORAL CRIME PREDICTION APPROACHES (RQ2B)

Crime hotspot detection and forecasting is an essential area of research due to the rapid increase in urbanization. The major shift is causing several challenges for law enforcement agencies to manage services and providing safety. Mainly, cities with highly populated areas the risk of crime can increase. Over the last few years, several efforts have been made in the area of crime forecasting [91], [99], [116]. This question aims to present the most promising techniques reporting so far.

Existing approaches for crime forecasting are divided into six different categories: Classical classification, deep learning-based, Clustering, Framework proposed, Regression techniques, and Time series analysis. Around 50% reported techniques for crime forecasting are standard classification, as shown in Fig. 8.

The detailed explanation, the dataset used, the comparison made, and the most promising technique reported in each study are presented in Table 12. From classical classification approaches mentioned above, random forest, hyper-ensemble, and M5P algorithm found to be superior as compared to other approaches. Deep learning-based approaches are reported extensively with the addition of Spatial and temporal information like Neural network (NN), Genetic algorithm with back propagation NN, Spatio-temporal NN based on LSTM, ST-ResNet, and Spatio-temporal CNN. Researchers have also attempted statistic and probability-based models as Spatio-temporal Ordinary Kriging, Linear discriminant analysis with K-NN, and Spatio-temporal generalized additive model.

Regression techniques have also been reported, like ridge regression and Support vector regressor. Clustering approaches constituted 40% of the total approaches and found to be promising. The clustering-based Superior approaches are also presented with some modifications like; DBSCAN, Cluster-Confidence Rate-Boosting (CCRBoost), Spatio-temporal Extended Fuzzy C-Means (SEFCM), and Clustered Continuous Conditional Random Field (Clustered-CCRF). One key aspect that is missing in all these approaches is the comparison with state-of-the-art techniques. The majority of the techniques failed to report

TABLE 12. Superior crime hotspot prediction techniques.

Study	Techniques Compared	Preeminent Technique
[116]	Cluster-Confidence-Rate-Boosting (CCRBoost) VS SVM VS Naïve Bayes VS C4.5 VS LAD tree	CCRBoost
[86]	LDA-KNN	LDA-KNN
[88]	GA-BP neural network model	GA-BP neural network
[117]	Negative binomial regression	Negative binomial regression
[90]	TCP VS Lasso VS ARMA	TCP
[118]	Regression techniques (Lasso VS Ridge)	Ridge Regression
[119]	Spatial point pattern test	Spatial point pattern test
[128]	Instance-based learning VS Linear regression VS M5P	M5P
[91]	Recurrent neural networks model	Recurrent neural networks
[13]	Deep learning using ST-ResNet	ST-ResNet
[93]	BayesNet VS Naive Bayes VS J48 VS Random Forest VS Decision Stump	Random Forest
[5]	Random forest Regressor VS Linear regression VS ARMA VS Clustered-CCRFD	Clustered-CCRFD
[17]	Autoregressive Integrated Moving Average model (ARIMA)	ARIMA
[125]	Cluster Confidence Rate Boosting algorithm	Cluster Confidence Rate Boosting
[100]	Random Forest VS Neural Network VS SVM VS Logistic Regression Model	Random Forest
[99]	Random Forest Regressor	Random Forest Regressor
[104]	Random Forest VS Logistic Regression AdaBoost VS Hyper-ensemble	Hyper-ensemble
[112]	ARIMA	ARIMA

a robust comparison with prominent techniques presented so far.

Recently time series analysis techniques have been presented [112], and it is evident that they outperformed as compared to state-of-the-art techniques. Particularly, ARIMA has been used for crime forecasting as it works best where the data have repeated patterns and trends. One drawback of ARIMA is that it cannot handle non-stationary data and takes much time in calculation. Crimes can be seasonal that may occur in a specific period and repeat that. So a research gap still exists to consider the seasonal element in crime forecasting and demographic factor that can affect crime.

2) PERFORMANCE MEASURES FOR SPATIO-TEMPORAL CRIME PREDICTION TECHNIQUES (RQ2C)

Six different categories of Machine learning and data mining approaches have been used in literature for Spatio-temporal

crime prediction, as mentioned above. Some studies have not mentioned any performance measure, and they also have not compared their proposed work with state-of-the-art techniques. It is hard to nominate one performance for crime hotspot detection because every technique has its context.

It is evident from the Table 13 that Accuracy and Root Mean Square Error (RMSE) are used widely for performance evaluation. The second performance measure is F1_score which is mainly used to evaluate classification algorithms. Precision, Recall, Sensitivity, and specificity also have been used for model evaluation. The Area Under the Curve (AUC) used in classification analysis and told us which models predict the models best. So the majority of the techniques used both Accuracy and RMSE to evaluate the performance of their models.

C. POTENTIAL CHALLENGES HIGHLIGHTED IN EXISTING STUDIES TO BUILD A ROBUST SPATIO-TEMPORAL CRIME PREDICTION MODEL (RQ3)

Several challenges need serious attention from researchers to build a robust Spatio-temporal crime forecasting model. One primary and most significant challenge in investigating crime forecasting is the accuracy and reliability of the data. It is evident from the SLR that more than 80 percent of studies failed to cite a dataset or even they do not describe its characteristics. It is assumed that if they provide some dataset, someone else may use it for the wrong purpose. Several factors can contribute to the limitations of the crime data.

The first barrier is under-reporting, where people do not report a crime. This is the primary reason that could not be added to the official statistics. A survey was conducted by the Malaysian and British police that approximately 50% failed to report the actual crime [129], [130]. Another constraint in crime data is the accuracy and reliability of data classification by the law and enforcement agencies.

Existing researches have been reported without the spatial and temporal information in the crime datasets [67], [131]. The last few years, with the inclusion of spatial and temporal information, urges the researchers to fill the research gaps and unmet needs of the law enforcement agencies. There are very few datasets that have been reported so far with the temporal and spatial information. The technological advancement in geographical information, such as the ArcGIS tool that is widely used for crime mapping helps the crime reporting agencies to overcome this issue. However, only 5 to 10 10% datasets are publicly available. 60% of the reported studies have presented their results on Chicago crime dataset [5], [89], [105] because it is publicly available. The proposed models lack in terms of generalizability because the model is trained in a particular area with a particular context. There could be several variations in demographic trends, cultures, methods of crime, and factors of crime across the countries. So, there is a dire need for transfer learning to identify potential areas and factors of crime that are common and to bring adaptability in the model.

TABLE 13. Evaluation measures reported for crime hotspot prediction.

Study	Techniques	Performance Measure
[116]	Cluster-Confidence-Rate-Boosting (CCRBoost)	Accuracy, F1_score
[86]	LDA-KNN	RMSE
[88]	GA-BP neural network model	Spearman correlation analysis, RMSE
[117]	Negative binomial regression	• Mean Squared Error (MSE)
[90]	TCP	RMSE
[118]	Regression techniques (Lasso VS Ridge)	Mean Squared Error (MSE), Predictive Efficiency Index (PEI)
[119]	Spatial point pattern test	Predictive Efficiency Index (PEI)
[128]	Instance-based learning VS Linear regression VS M5P	MSE, RMSE
[91]	Recurrent neural networks model	Accuracy, F1_score, Precision, Recall
[13]	Deep learning using ST-ResNet	RMSE, Accuracy
[93]	Random Forest	Accuracy, F1_score
[5]	Clustered-CCRFD	RMSE
[17]	Autoregressive Integrated Moving Average model (ARIMA)	RMSE, MAE, MAP, ME
[125]	Cluster Confidence Rate Boosting algorithm	Accuracy, F1_score
[100]	Random Forest VS Neural Network VS SVM VS Logistic Regression Model	Precision, Recall, F1-score
[99]	Random Forest Regressor	Accuracy, F1 score
[104]	Random Forest VS Logistic Regression AdaBoost VS Hyper-ensemble	RMSE
[112]	ARIMA	Accuracy, AUC

Transfer learning is an important area of research due to its ability to solve one task based on the experience of other related tasks. Traditional machine learning techniques are designed to solve a particular task. Recently, transfer learning has been used in different areas of research from traffic prediction [132] to financial time forecasting [133] and air quality prediction [134] etc. Transfer learning can be used for crime forecasting for areas with similar demographic trends and even for different countries. Transfer learning makes a generalized model that uses his experience and works well in the new setting.

Another critical aspect identified by the researcher is the inclusion of demographic factors while model building [99], [112]. It is suggested that by including demographic trends and events of the city, crime forecasting can be enhanced. It is assumed that crime has a positive correlation with the socioeconomic characteristics of demographic factors like; occupation, income, marital status, population, religion, birth rate, and death rate, etc. Some studies have also been reported

for crime prediction using Social media analysis and other factors [131], [135], [14]. Mainly, twitter data has been widely used for crime prediction. So, in future crime data, demographic factors and social network analysis can be used to make a robust crime prediction framework.

One major drawback identified from the proposed approaches is that majority literature failed to provide a robust comparison of the proposed technique with the state-of-the-art techniques. To make a robust Spatio-temporal crime prediction system, a reliable comparison should be made with the same experimental setup. It is also suggested that forecasting can be improved by expending time series analysis with SARIMA and some explanatory variables. Long short term memory can also be used with time series analysis to build a robust system.

D. WHAT TYPE OF DATASETS HAVE BEEN USED FOR CRIME PREDICTION (RQ4A)

The most significant problem identified in Spatio-temporal hotspot detection is the unavailability of the geocoded crime datasets. During the entire SLR process, it has been examined that a vast amount of literature failed even to cite the dataset. Some papers mentioned the details of the area covering the dataset but not cited them. Some researchers excuse in their papers that they cannot share the details of the dataset due to sensitive information provided by the police department.

This SLR aims to present the state-of-the-art datasets publicly available with all the necessary details for the researchers and beginners. Details of the datasets, along with the links, are shown in Table 14. It is evident from the Table that the Chicago crime dataset is widely used as it is geocoded and publicly available. Many researchers evaluated their proposed methodology on this dataset.

A dataset can contain different kinds of crimes reported by law enforcement agencies. It can be seen in Table 14 and a pie chart distribution in Fig. 9 that the researchers have widely used resident burglary crime type. It can be inferred from this information that resident burglary (40 %) is the most critical area that needs to be addressed. Secondly, to prevent street crimes (30 %), several methods have been proposed. Violent felonies and Homicide constitute 22 and 8 % respectively of the total crime types researchers have used.

Crime datasets presented in the literature are very few, and some are even have not the time and location information. So, there is dire need to present a Spatio-temporal labeled dataset and made it publicly available. There are very limited crime datasets of the Asia region, and the majority are not Spatio-temporal labeled. As crimes graph is different concerning time and location and geographical area and datasets are very limited. One technique can not be evaluated on society of certain norms and demographic factors. So crime datasets should be reported for different regions to predict crime that will help the agencies to provide a safer environment.
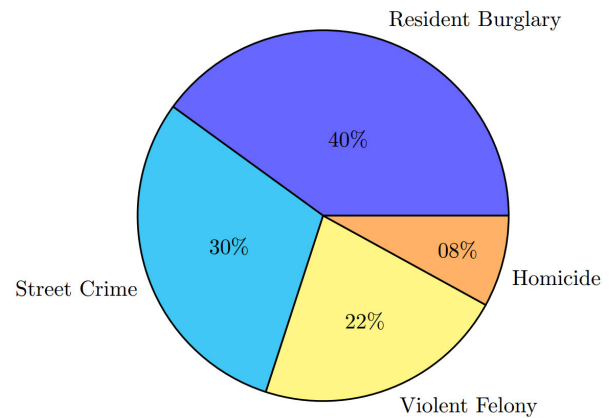

FIGURE 9. (%) Studies reported on specific crime types.

1) WHAT ARE THE MAIN ASPECTS OF A DATASET FOR THE SPATIO-TEMPORAL CRIME HOTSPOT? DO THEY AFFECT RESULTS? (RQ4B)

The police department professionally acquires the datasets presented in Table 14. However, there are some datasets mentioned in the Table that are not Spatial and Temporal labeled [71], [73], [74]. With the advancement in the GIS system, spatial and temporal information can be added along with the crime incident characteristics. From the past few years, the inclusion of spatial and temporal information in crime datasets urge the researchers to propose new and enhanced techniques for crime hotspot detection and prediction. Crime datasets acquisition is a critical mechanism that can affect the efficiency and robustness of techniques proposed by the researchers.

The reliability and accuracy of the crime datasets are the primary concern for researchers that is dependent on the Acquired authority. So, there is dire need to check the reliability of the dataset while performing evaluations. One preeminent aspect is the inclusion of spatial and temporal information of the crime incident. From the last few years, researchers [105]–[107] found spatial and temporal quiet helpful and proposed several techniques for crime hotspot prediction.

To make a dataset useful for crime prediction, it should be reliable, accurate, and Spatio-temporal labeled. Some crime events are reported by the police officers and sometimes by the people who are victims. The timely investigation can help them to collect all the relevant details; otherwise, the victim can forget some details. Law enforcement agencies need to conduct awareness and practical workshops for the officers about the GIS so that data acquisition can be made accurately. This will increase the prediction accuracy and efficiency of the crime events likely to occur in the future.

V. ANALYSIS

The primary objective of this SLR is to present and summarize existing techniques for crime prediction comprehensively. Specifically, it aims to answer the defined research questions by thoroughly reviewing the selected articles which were filtered using the inclusion, exclusion, and quality

TABLE 14. Spatio-temporal datasets and their characteristics used for crime prediction.

Reference	Link	Characteristics	Type	Geo Coded
[71]	Data freely available from the U.S. Bureau of Census. https://data.census.gov/cedsci/	Data included the offense date and time, offense type, police beat, and the address of the offense at the street block level	Street Crime	Yes
[74]	Taipei Police Department announce crime hot spots. https://english.police.gov.taipei/	Data comes from Taipei City Police Department announce crime hot spots	Street Crime	Not
[79]	http://dynamicinsights.telefonica.com/488/smart-steps	Crimes documented between January 1, 2013 and March 31, 2013, latitude/longitude coordinates of the crime at the cityblock level. same time period, collected tweets tagged with GPS coordinates falling within the city limits of Chicago	Street Crime	Yes
[83]	https://archive.ics.uci.edu/ml/datasets/	Information on several crimes in the USA, combining socio-economical and law enforcement data from 90' Census	Violent Felonies	Not
[84]	Crime records from Dhaka, Metropolitan Police Database. https://dmp.gov.bd/dmp-crime-map/	Not Available	Street Crime	Not
[91]	CFS data provided by the Portland, Oregon police bureau. https://nij.ojp.gov/funding/real-time-crime-forecasting-challenge	Call for service data	Resident Burglary	Yes
[92]	San Francisco Police Department, (SFPD) Crime Incident Reporting System focus only on violent felonies. https://www.kaggle.com/c/sf-crime	12 years (2003-2015) of crime records	Violent Felonies	Not
[99]	http://datasus.saude.gov.br/	13 urban indicators (including also the homicide indicator) from the year 2000 in our dataset that will be used as predictors of the number of homicides 10 years later	Homicide	Not
[100]	https://data.qld.gov.au https://data.cityofnewyork.us/Public-Safety/ https://www.census.gov/about/regions/new-york.html	Brisbane, the capital city of Queensland, Australia and the New York City, USA. Choose 6 same type of crime offense from both datasets	Resident Burglary	Yes
[9]	https://data.police.uk/about/ http://www.ons.gov.uk/census/2011	Official crime records that are published by the UK Police2 for 2015	Resident Burglary + Street Crime	Partially
[103]	https://vancouver.ca/police/	Data contain information pertaining to location, date, and time of occurrence for a number of property crime types (residential burglary, commercial burglary, theft of vehicle, theft from vehicle, other theft, theft of bicycle, and mischief), over a 16-year period, 2003 –2018	Resident Burglary	Yes
[104]	https://ec.europa.eu/eurostat/web/products-datasets/-/crim_off_cat	Dataset consists of burglary incidents in the Swiss canton	Resident Burglary	Yes
[105]	Crime data of Chicago www.urbanccd.org www.ci.uchicago.ed https://opendata.cityofnewyork.us/	Starting from the 'Crimes - 2001 to present' 295 dataset, we collected all crime events within the bounded area over 16 years (834 weeks), from January 2001 to December 2016	Violent Felonies	Yes
[106]	Crime data of Chicago www.ci.uchicago.ed	Use Subset of Attributes, Location Description Description, FBI Code, Block, Location, Year, Latitude, Longitude, Month, Day, Hour, Minute, Second, Primary Type	Resident Burglary	Yes
[110]	San Francisco Crime Data [https://data.sfgov.org/Public-Safety/Police-Department-Incident-Reports-Historical-2003/tmnfyvry] Chicago Crime Data [https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2] Philapedia Crime Data [https://www.opendataphilly.org/dataset/crime-incidents]	IncidentNum - Dates - Category - Descript - DayOfWeek - PdDistrict - Resolution - Address - Longitude of the location of a crime- Latitude of the location of a crime-Coordinate - whether crime id domestic or not- Arrested or not	Violent Felonies	Yes

assessment criteria. RQ1 and RQ2 are aimed to identify crime hotspot detection and prediction techniques along with performance measures used. In RQ3 potential gaps and challenges faced by the above techniques are thoroughly described that will help the beginners to start their research journey. RQ4 enlighten on the importance and aspects of the crime datasets should have.

The first task in crime prediction mechanism is to detect crime hotspot regions where crime occurrence is higher and active than other regions. Advancement in geographical information system gives a new horizon to crime hotspot detection by embedding spatial and temporal information in crime datasets. It also enables the researchers to mark the hotspot regions and efficiently analyze and visualize their respective change. RQ1 is formulated to identify the crime hotspot detection approaches reported for the last ten years and prominent approaches among them, along with the performance measure used.

It is evident from the Table 8 that several machine learning and data mining approaches have been attempted for crime hotspot detection. However, clustering and classification approach found to be more useful in crime hotspot detection. Precisely, Random forest [92] and DBSCAN [112] algorithm has been reported recently and compared with state-of-the-art techniques and found to be efficient and effective. Researchers are still facing the accuracy gap provided by these techniques. They aim to overcome the limitation of the recent developments in crime hotspot detection so that it can be implemented in the real world.

Efficient crime hotspot detection enables a machine learning to learn the proximity of a crime so that it can be predicted in future. In this regard and based on crime prevention importance by predicting crime, several techniques have been presented and implemented in different areas of developed countries. Again, data mining and machine learning approaches, specifically time series analysis techniques, have been widely used for crime prediction. From the last many years, classification and clustering algorithms have been used in a significant number for predicting future crime. Nevertheless, these approaches alone were not so reliable and practical to implement in the real world. Recently time series analysis gave a breakthrough in crime prediction by boosting the prediction mechanism.

Time series analysis is derived from the statistical and econometrics area collectively to understand and predict the future occurrences from the time series data. Mainly, ARIMA [112] has been used recently with the Spatio-temporal crime data for crime prediction and outperformed the state-of-the-art techniques. ARIMA models have been widely used in literature for forecasting of different real-world events like; energy consumption [136], inflation [137], wind speed [138], and economics [139] etc. However, the problem with the ARIMA is that it cannot capture the seasonality and repeated behaviour of event, especially crime events. So an enhanced forecasting algorithm should be in place to predict crime event efficiently by resolving seasonality factor.

Several performance measures have been used in the literature to evaluate the performance of crime detection and prediction algorithms. The purpose of studying different performance measures used in the existing literature is to come up with the most reliable and widely used measures so that the beginners can follow a standard measure. This will also help a researcher to compare the accuracy and efficiency of his algorithm with the state-of-the-art techniques in the same experimental setup with the same performance measures. The most widely used performance measures are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Error (ME), and Root Mean Square Error (RMSE).

RQ3 discusses the potential challenges faced by the researchers and potential techniques. It aims to identify the potential gaps so that a new researcher in this field can easily understand the unmet needs and act on it. Several potential areas have been identified for future research throughout this SLR and pilot study process such as; use of transfer learning [15], [140], [141] enhancement of crime hotspot detection algorithm(DBSCAN) for boosting detection accuracy, enhancement of crime forecasting algorithm (ARIMA) for prediction accuracy improvement, Long Short Term Memory (LSTM) with exponential smoothing [139], [142], the inclusion of demographic factors, and social network analysis etc., for crime prediction as shown in Fig. 10.
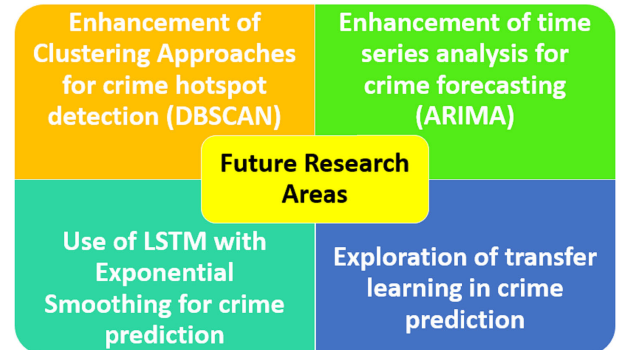

FIGURE 10. Potential areas for future research.

The most essential and prominent aspect of crime prediction is the labelled spatio-temporal datasets. It has been noticed during this SLR that the majority of the studies failed to cite the datasets and some are not publicly available. Some studies have excused that due to sensitive data and agreement by the respective police, they cannot share the details of the datasets. The two most widely used and publicly available datasets are Chicago [106] and New York city datasets [105]. RQ4 formulated to emphasize the importance and necessity of more publicly available datasets. So a researcher can contribute to the body of knowledge of crime prediction by presenting a novel datasets. This SLR concludes by enlightening on the reliability, accuracy and timeliness issues of crime datasets that can affect the overall performance and efficiency of crime prediction algorithms.

VI. CONCLUSION AND FUTURE STUDY

In this study, we systematically unfold the critical aspects of crime hotspot detection and prediction mechanism by following the guidelines of Kitchenham and Charters [25]. This is the only SLR presented to the best of author's knowledge from the last ten years that summarize and organize the scattered shreds of evidence in the area of crime prediction. Notably, this SLR performed to investigate the unmet needs and future directions from 49 selected research articles published from January 2010 to December 2019.

The primary objective of this research is two-fold. First, it focuses on crime hotspot detection approaches presented so far and identify the most leading and effective approaches among them, along with the performance measure used. It is evident from the Table 9 that DBSCAN and Random forest are found to be useful and efficient in terms of accuracy and efficiency. However, several limitations were identified [143] during the SLR that crime hot spot detection algorithm should be; scalable, can deal with sparsity, underlying population, and demographic factors, etc.

Secondly, crime prediction strategies have been analyzed comprehensively. Several data mining and machine learning approaches have been applied but failed to perform in the real-world. Recently, the time series analysis area has been explored by the researchers for crime prediction and found to be comparatively efficient. Correctly, ARIMA has been used in forecasting different real-world events like; energy consumption prediction, economic trend, and air pressure, etc., although it can predict on the data that indicate trends. Nevertheless, for crime prediction, ARIMA models need improvement for handling crime that exhibits seasonal and repetitive behavior in nature. In the future, a prediction algorithm may consider the social network connection, geotags, social networking posts, and trends of crime with the events in a particular city.

This SLR concludes that crime hotspot detection and prediction is a crucial process that needs further investigation. Several important research areas are identified during this systematic process that will helps the researchers to build an enhanced and more robust crime prediction system. Additionally, novel spatio-temporal datasets should be produced to enhance the effectiveness of the proposed approaches, and a region must have a dataset so that crime prevention strategies can be made that will boost the growth of a country.

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