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A Systematic Review on the use of Machine Learning and Deep Learning Techniques for Crime Prediction from Social Media

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Abstract: The goal of crime prediction is to help law enforcement authorities to prevent crimes before they happen by identifying and reducing potential future crimes. In present days, crime cases are rapidly occur so it is a challenging task to accurately predict and classify the future crimes, as criminal patterns are adaptable and constantly evolve, making it a challenging task. Sentiment analysis is essential for deciphering the feelings conveyed in text since social media has grown into a popular venue for individuals to communicate their thoughts, feelings, views, and comments. This analysis is particularly valuable for making informed decisions in business, politics and government agencies especially to identify crimes. However, it faces the difficulties like lexical diversity and dataset imbalance. In order to make better decisions and maybe lower the risk of predicting the suspects in a crime, early crime prediction has lately made use of Artificial Intelligence (AI) models like Deep Learning (DL) and Machine Learning (ML). When applied to crime data, ML and DL models may assist pinpoint possible crime hotspots and foretell when crimes may occur. Crime prediction and categorization using social media posts is covered in depth in this paper, which offers a comprehensive overview of several ML and DL frameworks. Initially, different ML and DL based crime prediction models designed by many researchers are examined in brief. The next step is to do a comparison research to learn about the shortcomings of those frameworks and provide an alternative method for effectively predicting crimes based on social media postings.

Keywords: Crime prediction, Machine Learning, Deep learning, Social media, Decision Making.

I. INTRODUCTION

A disturbing and pervasive part of society is crime. There are a lot of crimes committed every day, and the regular occurrence of these crimes has made regular people anxious [1]. Because of the dynamic nature of crime patterns, it is challenging to provide consistent explanations for observed behaviors. Through the use of Information Technology (IT), law enforcement authorities are able to gather data about criminal activity [2]. However, it is impossible to anticipate when a crime will occur, and prior research has shown that variables such as poverty and unemployment impact the crime rate. Neither is it random nor is it uniform. Predicting future crime rates is becoming more difficult since the number of crimes continues to rise at a fast speed [3].

The traditional approach to crime prediction makes use of demographic data from hot-spot maps and historical socio-economic indices to foretell where certain crime kinds will be most prevalent [4]. For crimes like taxi robberies, where victims could be located anywhere in the country, these maps might not provide the most reliable representation of the crime scene [5]. Because of the inherent limitations of using criminal records from one place to another, there is a severe shortage of data for use in prediction models. The biggest problem is that these techniques don't take neighborhood socio-behavioral data into account; they just look at past crime statistics [6].

The ability for users to publicly debate and broadcast their ideas, problems, and sentiments on social media platforms such as Instagram, Facebook, Twitter, and the like is expanding at a rapid pace. It is possible to deduce the user's mood and the text's contextual polarity from these social media posts' concealed information [7]. They extract useful socio-behavioral signals from user-generated material and transform them into textual data that sheds light on users' day-to-day lives. The data presented in these unstructured postings has great potential for use in crime prediction [8]. As a subfield of Natural Language Processing (NLP), sentiment analysis (also called opinion mining) seeks to discover, extract, and categorize subjective information from unstructured text by use of text analysis and computational linguistic approaches. Sentiment analysis relies on contextual clues within words to determine the polarity of a statement. The significance of sentiment analysis, recognized widely, lies in its effectiveness as a tool to extract valuable insights from sources such as reviews and tweets [9].

In recent times, the application of sentiment analysis for crime prediction has emerged as a practical approach. By employing sentiment analysis techniques on various data outlets like social media posts, news articles, or online reviews, valuable insights regarding public attitudes, emotions, and opinions on crime can be derived [10]. Sentiment analysis involves the identification and categorization of text based on positive, negative, or neutral emotions, providing a nuanced understanding of the prevailing sentiments associated with criminal activities or specific areas. The incorporation of sentiment analysis into crime prediction models empowers law enforcement organizations to enhance their comprehension of public perceptions of safety and optimize resource allocation [11]. In addition, sentiment research has the potential to help identify emerging crime trends prior to their official announcement, enabling communities to take preventative measures to ensure the safety of their residents. However, sentiment analysis cannot be applied to high-dimensional and complexing enquires in crime data. Also, it faces challenges such as lexical diversity and dataset imbalance [12]. Fig. 1 shows the general work flow of ML and DL model.

In recent times, AI models like ML and DL plays a vital role in the prediction and classification of crimes [13]. Both these models are powerful tools in learning useful features from the user's sentiments and emotions form the social media post. ML is a branch of AI concerned with data analysis and prediction using statistical models and algorithms. In order to assess crime data and forecast future crime trends, ML are used in crime prediction [14]. Certain ML algorithms, such as Decision Trees (DT), Random Forests (RF), and Support Vector Machines (SVM), undergo extensive training on crime data from specific cities. This training equips them to accurately predict crime patterns within those particular areas [15]. To find crime hotspots and forecast future occurrences, ML models may examine crime data in particular geographic regions. By using this data, law enforcement may better allocate their resources to regions where they are most needed [16]. But, ML models struggle with large datasets and when input is provided in a continuous range, their accuracy decreases emphasizing their limitation.

DL Models are an advanced version of ML which have been greatly enhanced the prediction achievements in various domains such as health, business, agriculture, law enforcement and so on [17]. DL algorithms hold the potential to significantly enhance the ability to analyze and recognize crimes in real-time, providing a crucial tool in the ongoing fight against criminal activity. DL models are employed to scrutinize surveillance footage, enabling the detection and classification of criminal activities such as vandalism, theft, and assault. Furthermore, these models are integrated with drones and aerial technologies to enhance monitoring capabilities and facilitate improved responses to criminal activities [18]. DL algorithms, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), among others, have demonstrated promise in the realm of crime prediction. These advanced neural network models showcase potential in analyzing complex patterns within crime data, contributing to more accurate and insightful predictions [19]. To reliably forecast crime trends in particular cities, these algorithms have been trained using crime data that includes both geographical and temporal components. To better understand where crimes are most likely to occur and when they will occur, DL algorithms may be used to a variety of crime data sets, such as time, location, and kind [20].

A wide range of articles have been using ML and DL methods for crime prediction and classification have yielded promising solutions to reduce the crime activities and analyze the crime trends leading to earlier preventions in the society. Fig. 2 shows the pipeline of ML and DL based crime prediction system. The primary objective of this paper is to offer a comprehensive overview of recent advancements in ML and DL based crime prediction models that leverage social media data for the swift identification of crime hotspots and accurate forecasting of future incidents. Additionally, a comparative study is presented to evaluate the strengths and weaknesses of these frameworks, providing insights for future research directions. The subsequent sections are organized as follows: Section II delves into various ML and DL frameworks specifically tailored for crime prediction and classifications. Section III conducts a comparative analysis of these frameworks. Finally, Section IV summarizes the entire survey and outlines potential areas for future exploration.

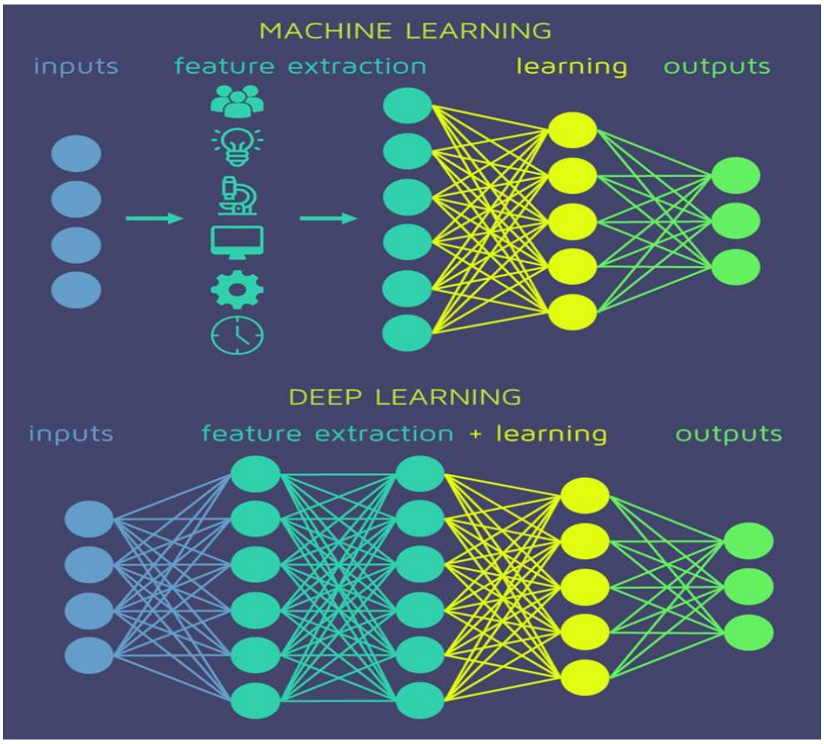

Figure 1. General Work Flow of ML and DL Model

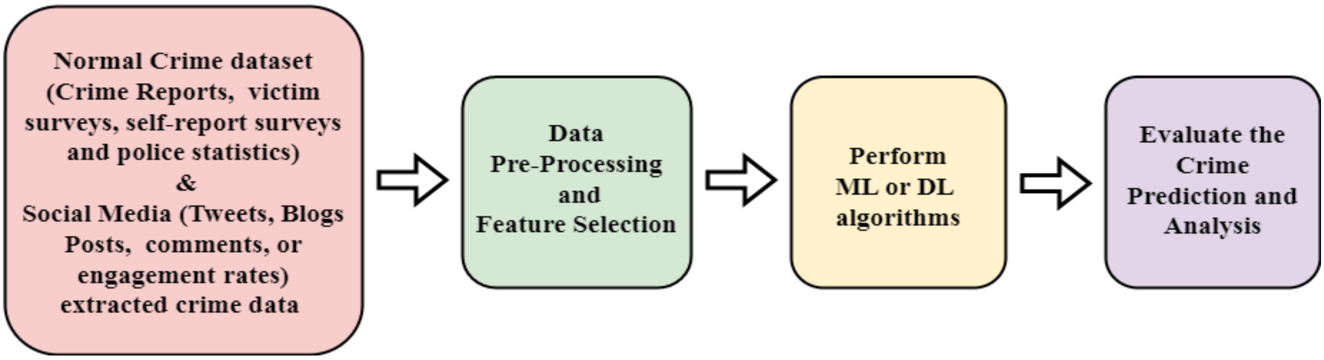

Figure 2. Pipeline of ML and DL Based Crime Prediction System

II. SURVEY ON CRIME DETECTION AND CLASSIFICATION USING MACHINE AND DEEP LEARNING MODEL

A kernel density estimation (KDE) was developed to detect and classify the crime using twitter data [21]. This approach analyzed tweets for crime detection using text processing technologies and related parameterizations. Automated topic detection for crime in the city was achieved via the application of statistical topic modeling and Twitter-specific language analysis. Lastly, KDE was used to forecast particulate city violence.

To predict the incidence of crimes that takes environmental context information into account using multi-modal data fusion [22]. This model consist of three structural components for crime prediction. Initially, the statistical analysis was used for data selection and multi-modal fusion model. The proposed model employs a Deep Neural Network (DNN)-based prediction model that incorporates feature-level data fusion, enhancing accuracy through the direct concatenation method. The model were structured with four layer groups, including spatial, temporal, environmental context, and joint feature representation layers. This comprehensive architecture ensures the precision and effectiveness of crime occurrence predictions.

A crime hotspot prediction model named CrimeTelescope, utilizing a fusion of urban and social media data [23]. Through the amalgamation of various urban and social media data types, this method visualizes and predicts crime hotspots effectively. Then, the key features were retrieved form the collected based on linguistic and statistical evaluation using Latent Dirichlet Allocation (LDA). Lastly, the regression model was used to assess the crime hotspots. It took use of the attributes that had been collected and produced representations of the hotspots on an interactive map that could be used for crime prediction.

A crime prediction model was built [24] using a model based on DNN. The approach used data modeling based on dynamic windows to forecast the individual's likelihood of committing a new offense within a certain time period. The data pooling method (DPM) was used to analyze all possible historical crime performed by a person for particular years. Finally, DNN was utilized for most effective multi-class crime predictions.

The implementation of BERT model [25] was used to detect crime-related Twitter posts. The process began with the pre-processing of collected data, transforming it into vectors to generate feature vectors. Subsequently, pre-trained word contextualized embedding techniques, utilizing the Transformer architecture, were employed to create word vectors. Finally, the BERT model was applied for crime detection.

To develop a system for detecting crime rates across various crime locales on social media using Twitter's part-of-speech tagger and brown clustering [26]. In order to understand the users' mental processes and behaviors in relation to the criminal activities, sentiment analysis was used on their tweets. The part-of-speech in online conversational text was tagged using Twitter's version of the Markov model, which is based on first-order entropy. For the purpose of crime rate prediction, brown clustering was applied to a lengthy collection of unlabeled tweets containing actual crime rates according to various places, as collected from an approved source.

To develop ANN+BERT [27] based crime detection and prediction system using meteorological data and tweets. The two parts of this model are the criminal detection and prediction sections. To generate the word vectors, the acquired data was pre-processed using pre-trained word contextualized embedding methods. The detection of tweets pertaining to criminal activity was carried out using a BERT-based method. Then, an ANN that can detect tweets about criminal activity was used to build the prediction module.

Some ML frameworks [28], to demonstrate an automated system for classifying criminal tweets and predicting their geolocation. This model extracts the real-time tweets using the Twitter Streaming API. The tweets were pre-processed to eliminate the punctuation, stop words and URLs. Then, the tweets were classified using an emotions and hash tags as sentiment labels using Natural Language Programming (NLP) model. Finally, Naïve Bayes (NB) techniques were employed to effectively categorize the crime labels for the efficient crime prediction.

To develop a DNN [29] based crime prediction using twitter data. This framework consist of three modules. Initially, the tweet data regarding the particular crime were extracted. Then, the collected data was pre-processed and normalized using different geometric models. Finally, LSTM model was used for crime prediction and classification.

To construct an AI model for the crime discovery rate prediction using the twitter data [30]. The user interactions and behavioral patterns were determined by using the graph analysis and meta-data methods from which the timeline of each profile and time-series behavioral features of users. The irrelevant behaviour detection and filtering components were performed to select the interesting profiles for preceding analysis. The contents were evaluated using NLP and binary text classification model called SVM + Term Frequency-Inverse Document Frequency (TD-IDF) were employed to predict the crime from the tweets.

To construct a DL [31] structure for crime classification and prediction. This method classifies each cell as a hotspot for a specific crime type in a monitored city's neighborhood with the highest spatial resolution. Hotspots were predicted and ranked based on crime numbers to efficiently allocate resources. The secondary parallel prediction was used for each crime to increase the probability of an area being a crime hotspot. Finally, CNN model were employed to extract the spatial and temporal information form the hotspot to predict and classify the crimes.

As a hybrid sentiment analysis method for criminal identification, model using [32] BERT method, which stands for Bidirectional Encoder Representations from Transformers. In this method, Spark Natural Language Tool-Kit (SNLTK) was used to break sentences into words and tag them. This model computed the sentiment score of each sentence using dictionary vocabulary. The extracted data was pre-processed using the BERT model. The pre-trained model was employed to construct the model and tokenizer which was then fine-tuned using the labeled Twitter dataset for crime prediction.

To develop a federated LSTM (F-LSTM) [33] model for time series crime prediction. In this method, the collected data from the crime tweets were pre-processed and augmented. Then, the pre-processed data were given as input to the F-LSTM for the time series crime prediction. The performance of F-LSTM was better than traditional LSTM in detecting the long-term dependencies for predicting the crimes with lower computational complexity.

An unsupervised domain adaptation model (UDAC) was proposed [34] for the purpose of predicting crime risk across cities. At first, for every target city grid, a number of source city grids that were somewhat comparable were identified. In order to make the two cities' contexts more uniform, the source city grids were used to create supplementary contexts for the targeted city. For precise criminal risk prediction, an unsupervised domain-adapted dense convolutional network was trained to learn both domain-invariant features and high-level representations concurrently.

To develop a crime detection and analysis using ML and NLP models [35]. Assaults, hate speech, insulting communications, and messages pertaining to drug crimes were all identified using the methodology. For text tokenization, stemming, and lemmatization, natural language processing methods were used. SVM and RF classifiers were used to classify and detect crime from the texts.

To construct a spatio-temporal crime detection on twitter data using ML models [36]. The required tweets were scraped from Twitter using the search feature of the tweepy module, utilizing the aggregated dataset. The data collection was then cleaned to remove duplicate tweets and improve its integrity. By prioritizing the exploration of tweet properties, the location identification was carried out to determine the geographical location of the crime. Last but not least, the LSTM model was used to ascertain the criminal tweet count time series forecasting for crime detection.

A Modified Capsule Network (MCN) including crisscross optimization was proposed [37] for use in cyber-crime security sentiment analysis prediction. Using a rule-based approach, the method combines the outputs of MCN and Multilayer Perceptron (MLP) networks, allowing them to work together to enhance the detection rate. After that, the hyper-parameters of the capsule network were fine-tuned for crime prediction using the CCO approach.

To develop a pre-trained CNN for crime intention detection using object detection [38]. In this method, the collected data was pre-processed and normalized. The pre-processed data would be fed into VGG-19, ResNet and GoogleNet for the crime rate prediction and classification. Moreover, the YOLO was introduced to identify the objects along with crime prediction.

An agent-based model (ABM) [39] was created by projecting future criminal behavior to inform public safety policy. This technique was based on the idea that different urban features, such as criminals, residents, and police personnel, interact to produce certain crime cycles. In order to forecast criminal tendencies and locate trouble spots in the city where security may be enhanced, this approach examines the criminal's actions by giving details such as their escape routes and the frequency of thefts. Considering environmental data allowed us to develop a defender's position and crime factor, which helped us determine the optimal defender's positions to reduce the city crimes.

A multimodal DL crime prediction system that utilizes tweets was developed [40]. The technique trains a crime prediction model using semantic knowledge of the text domain and data on past crimes. Using the ConvBiLSTM model, we were able to merge the tweet and crime modalities into a single representation after extracting independent vectors from each. To train language models, we used word embedding vectors using crime and twitter data, and then we used convolution and pooling layers to summarize the meaning. The vector characteristics were fused using the deep crime-semantic model, which trained on both crime and twitter data to predict crimes.

III.EASE COMPARATIVE ANALYSIS

This section follows a comparison of the aforementioned crime prediction models that use social media data and are based on ML and DL models. The table 1 provides the compassion of different crime prediction models using ML and DL algorithms are listed.

Table. I Comparison of Different ML and DL Based Crime Prediction Models

Ref No	Techniques	Advantages	Disadvantages	Performance Metrics
[21]	KDE	This model enhances the allocation of limited resources, resulting in a reduction of wasted effort and a decrease in crime response times.	This model do not properly account for temporal effects such as trends, lags and periodicity	AUC = 0.65;
[22]	DNN	Effectively analyzes the relationship between environmental context information	It was limited to regions with insufficient data, potentially causing performance degradation.	Accuracy = 84.25%; Precision = 74.35%; Recall = 80.55%
[23]	LDA, CrimeTelescope,	Reduce ambiguity and effectively reconsider the factors that	This model was insufficient to handle the large crime databases	Accuracy = 0.82; AUC = 0.79;

	Regression model	influence particular crime categories.		F1-Score = 0.8;
[24]	Data pooling method, DNN	This model works well on large and smaller data while complexity reducing the overfitting issues.	This model struggled to capture contextual information and word relationships	Accuracy = 97.6%; F1-Score = 87%
[25]	BERT, word contextualized embedding techniques	Completely optimized, less memory space and computational time	This model does not train comprehensive spatiotemporal features from various sequences and it was not effective at fusing the complementary features of multiple sequences.	Accuracy = 92.8%; Precision = 96%
[26]	Markov Model, Brown Clustering	Lower computational issues and works well on larger dataset	This model did not effectively capture semantic features and long-term dependencies among crime tweets	Accuracy = 100%; Precision = 98%
[27]	ANN+BERT	Better convergence rate, scalability and handles high dimensional data	This model was easy prone to overfitting, redundancy, and dependency on multiple datasets	Accuracy for crime detection = 91.5%; Accuracy for crime prediction = 81.85
[28]	NLP, NB	This model was scalable and robust while performing on large scale dataset	Slower convergence rate was determined	Accuracy = 82%; Precision = 83.7%
[29]	LSTM	Structure of the model was simple and easy to implement for crime reviews	The data interpretation was inadequate, leading to easy overfitting issues.	Accuracy = 82.6%; Precision = 86.4%; Recall = 80.4%
[30]	AI, SVM-TD-IDF	This model effectively handle overfitting and data imbalance problems.	It takes ling time to train the larger datasets	Accuracy = 88.89%;
[31]	CNN	High scalability and better convergence rate	This model's generalizability was subpar due to the inability to evaluate the reported dataset with the large network's data volume.	F1-Score = 0.94; Area Under Curve (AUC) = 0.95
[32]	BERT, SNLTK	It does not effectively capture the semantic features and long-term dependencies among tweets	Fine-tuning the BERT model was also difficult and required substantial amounts of task-specific data	Accuracy = 97.24%; Precision = 92%; Recall = 94%, F1-score = 93%,
[33]	Federated LSTM	The model's parameters were optimized to determine lower loss and higher accuracy	Trained with limited amount of dataset	Mean Absolute Error (MAE) = 0.102; RMSE = 0.43
[34]	Dense convolutional network with unsupervised domain adaptation	Effectively reduces and resolves the distribution discrepancy among two cities contexts	This model results with high data sparsity issues and serious context conflicts arises between the source and target cities	MAPE = 0.156; Execution time = 0.5s
[35]	NLP. SVM, RF	Eliminates noisy, irrelevant data and devises quick response time	This model takes long time to train the collected data	Accuracy = 86%
[36]	LSTM	This model collectively determines the most likely locations for crime at any given time throughout the country.	It doesn't consider the tweet contents to determine the accurate interaction among the users, which might impact the predictive decision.	RMSE = 7.78; MAE = 6.29
[37]	MCN-MLP, CCO	Better Generalizability and can be applied for real time applications	Slower training time and easy prone to overfitting issues.	Accuracy = 92%; Precision = 94.2%;

				Recall = 93.7%
[38]	VGG-19, ResNet GoogleNet and YOLO	Rapid Response time, provides early warning system and lower memory space	Optimization algorithms were highly necessitated to fine-tune the parameter of the pre-trained CNN models which leads in uncertinity issues.	Accuracy = 0.91; Recall = 0.91; F1-Score = 92.6%; Inference speed = 68
[39]	ABM	High Scalability and applied as real time mode to minimize the crime frequency in the city	High computational cost and necessities some advanced models to improve the detection efficiency.	MSE = 0.103;
[40]	ConvBiLSTM, Deep crime-semantic model	Effectively minimizes the feature number to eliminate overfitting simultaneously reducing time and parameter complexity.	The study was constrained to English tweets specifically related to theft, battery, burglary, robbery, and motor vehicle theft.	Accuracy = 97.5%;

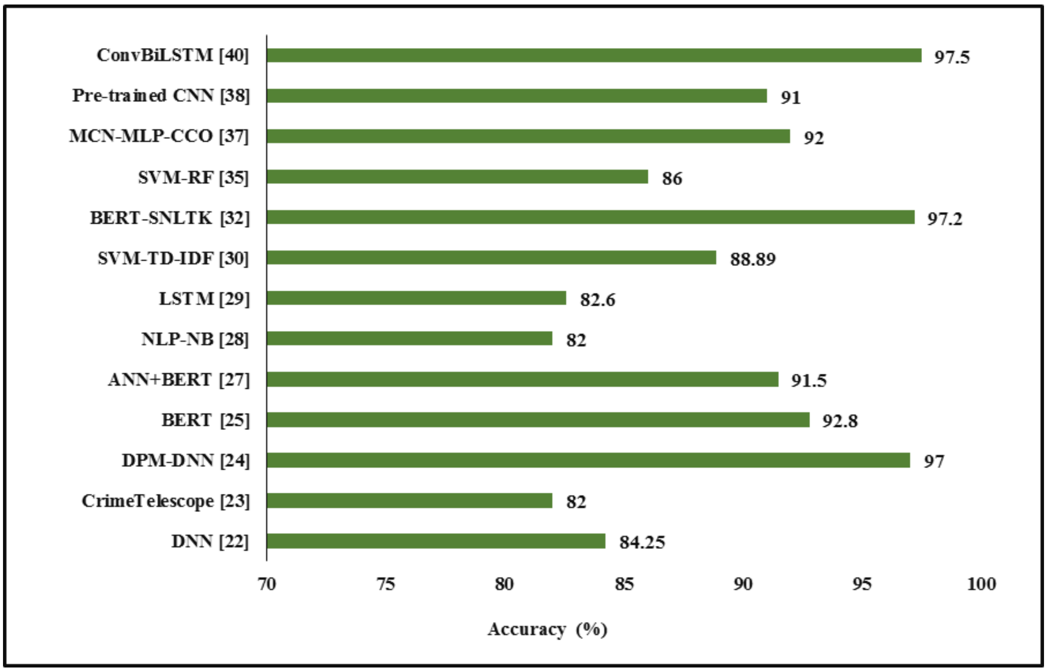

Figure 3. ML and DL Based Crime Prediction Using Various Social Media Data

IV. PERFORMANCE EVALUATION

The performance review of the exiting ML and DL methods listed in Table 1 in order to showcase the accuracy of overall prediction and classification of crime. In this section, the performance of various ML and DL based crime prediction models are compared in terms of accuracy. The below provided graphical representation in Fig. 3 shows the effectiveness of a model for crime detection and classification based on various social media post and blogs.

The Fig. 3 shows the ML and DL based crime prediction model. From the above figure, it is observed that the article [40] yields better prediction result for crime prediction using tweets. By combining real-time tweets with crime data, the authors of the study [40] create DL multimodal crime prediction, which uses data fusion to overcome the shortcomings of earlier crime model research. This approach takes a vector-level look at both tweets and crime modalities to get their word features, which are then combined into one representation. Additional training was conducted using ConvBiLSTM, which traverses the data twice, once from left to right and once from right to left. This allows it to extract the word vector from the sequential data while keeping it in context with the information that came before and after it. As a result, ConvBiLSTM is able to capture long-term contextual dependencies and global features. Word embedding vectors also pick up the language model from tweets and crimes. A deep criminal-semantic model's convolution and pooling layers distilled the tweet's meaning and the crime data into a single representation. In order to train them to anticipate crimes, this representation incorporates the vector feature that captures information from both crime and tweets data.

V. CONCLUSION

This research presents a comprehensive comparison of crime prediction models that rely on several ML and DL models. Crimes are increasing rapidly, requiring efficient interceptive measures. Traditional crime-solving techniques are slow and less efficient, making it crucial for agencies to develop efficient methods. In recent days, ML and DL models have been applied to analyze the social media data in detection and prevention of crime ensuring the safety and security of communities by law enforcement. This paper conducted a comprehensive review of different ML and DL methods for crime prediction according to their strengths, weaknesses and detection efficiencies. In order to make better use of their resources, anticipate crime at a specific moment, and serve society better, researchers may use this review to determine the most efficient and reliable detection techniques for recognizing criminal episodes and their patterns. Future work will focus on developing advanced DL models for law enforcement agencies to implement intervention and on-spot practices, avoiding complications and burdening the enforcement systems.

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