Crime Prediction Using Modified Capsule Network with CrissCross Optimization on the Sentiment Analysis for Cyber-Security

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Abstract. Data mining from textual sources is known as social media text analytics. Social media, like any other text-based dataset, is amenable to text analysis. Today's society has a huge challenge in the form of crime, with the routes of which having shifted almost entirely to social media. Because of crime, both the standard of living and economic development have suffered. By sifting through the available data, we may identify trends in criminal behaviour and foresee potential incidents in the future. Unfortunately, not all crimes are recorded or solved due of a lack of evidence. Hence, tracking these offenders remains challenging. We can keep an eye on illicit activities on social media. For the simple reason that social media users sometimes make observations about their immediate environment. In this study, we propose a model for crime categorization on a Twitter dataset that combines the recently proposed Capsule Network with the tried-and-true Multilayer Perceptron. The output of both networks is combined in a manner that makes the most of each network's strengths using a rule-based technique. Moreover, the Criss-Cross Optimization (CCO) method is used to fine-tune the capsule network's hyper-parameters. Crime statistics from reliable sources are used to make accurate comparisons between regions. We also evaluate recent changes in crime rates in both Jammu, India, and Ghaziabad, Uttar Pradesh. The most recent crime patterns during the last week have been documented (23, January 2019 to 30, January 2019). The studies show that the generated findings are consistent with the actual crime rate information. We anticipate that research of this kind will aid in gauging the current crime rate in various areas and in identifying criminal activity.

Keywords: Criss-Cross Optimization · Social-media · Capsule Network · Multilayer Perceptron · Criminal activity and in identifying criminal activity

1 Introduction

Criminal activity has far-reaching, deleterious effects on many elements of our society and culture. Recognizing high-crime areas and pinpointing the most recent incidents in a given area is a major problem for both local authorities and private citizens [1].

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On the other hand, city dwellers are always working to make their communities safer and friendlier places to live. The prevalence of crime is one of the most pressing issues confronting modern societies [2]. There have been much less research using social media to examine crimes and criminal behaviour than there have been on social crimes. Our primary data comes from social media. The real-time social networking platform Twitter has exploded in popularity throughout the globe. More than 300 million people throughout the globe use Twitter, and more than 500 million tweets are sent per day, according to data [3].

Using tweets for personal, professional, and business purposes is a terrific way to stay in touch with loved ones and co-workers [4]. Cyberstalking, cyberbullying, and other forms of cyber harassment are only some of the difficult problems that come up when people use Twitter. Data is collected from a social media platform by the use of a small number of sensitive terms [5, 6] associated with the crime, Assault. Among a significant volume of tweets, 3801 are selected to serve as datasets for the research. During the course of four years, a great deal of tweets are filtered out using keywords. The non-alphanumeric characters have been cleared out of the data [7]. Recognizable crime rates have also been acquired from security agencies, and a major component of our research involves comparing the datasheet built from Twitter data with the actual crime data conventional from security units [8, 9].

For seven predetermined locations in India (Ghaziabad, Chennai, Bangaluru, Chandigarh, Jammu, Gujarat, and Hyderabad), Twitter data represents the number of Tweets recorded using various keywords such as "Murder "Rape," and "Fight" between January 2014 and November 2018 [10]. A total of 3801 Tweets were gathered for this study and stored in a database. The correctness of the current study may be verified by comparing the predicted crime rates with actual crime rates obtained from security authorities (such as the National Crime Records Bureau, http://ncrb.gov.in/). There are a lot of people trying to figure out how to forecast a user's rank based on their social media account, and they're all working in various areas of social networks [12]. Measures of centrality and the structure of networks have been studied. Algorithms based on random walks and diffusion have been shown as viable methods for rating social media nodes [13, 14].

2 Related Works

Sivanantham et al. [16] Sentiment analysis' primary function is to examine customer feedback and assign ratings accordingly. The evaluations are generally unstructured, which means they need to be categorised or clustered in order to give useful data for the future. In order to improve the categorization accuracy in kid YouTube data emotional analysis, this study gives an overview of numerous machine learning algorithms. The sentiment analysis of children's videos on YouTube is improved by using a hybrid Support vector machine model trained with the ant colony optimisation approach. The paper examined Naive Bayes, SVM, and Adaboosting + SVM classification methods, and the findings were used to develop the suggested hybrid classifier. Each classifier's prediction for a set of test words submitted by children from YouTube is collected, and the classifier with the least detrimental and most secure prediction is proclaimed the winner. The suggested hybrid strategy outperforms both stand-alone machine learning algorithms and previously proposed hybrid approaches in terms of classification accuracy.

Using a hybrid method, Gautam and Bansal [17] established a system for real-time, automated cyberstalking detection on Twitter. First, lexicon-based, machine learning, and a hybrid approach were tested using recent, unlabeled tweets gathered through the Twitter API. All of the approaches that were utilised to extract the feature vectors from the tweets relied on the TF-IDF feature extraction technique. The best results from the lexicon-based procedure reached 91.1% accuracy, whereas the best results from the machine learning approach hit 92.4%. In contrast, when identifying unlabeled tweets retrieved through the Twitter API, the hybrid method showed the greatest accuracy at 95.8 percent. The machine learning method outperformed the lexicon-based method, and the suggested hybrid method performed very well. The real-time tweets acquired by Twitter Streaming were again classified and labelled using the hybrid technique with a new approach. The hybrid method again delivered the highest results as predicted, with an AUC of 98%, a precision of 94.6%, a recall of 94.1%, and an F-score of 94.1%. Machine learning classifiers' efficacy was evaluated across three distinct labelling strategies on each dataset. According to the study's experimental findings, the suggested hybrid technique outperformed previously applied methods in classifying both historical and real-time tweets. SVM outperformed competing machine learning techniques across the board.

2.1 Data Collection

2.1.1 Twitter Data Collection

From January 2014 to November 2018, information was culled from Twitter profiles by manually browsing through search results for profiles based in seven cities throughout India (Ghaziabad, Chennai, Bangaluru, Gujarat, and Hyderabad). Table 1 provides the latitude and longitude of potential study sites (extracted from Google Map Online).

Table 1. Seven different crime locations in India.

Location	Latitude and Longitude
Ghaziabad, India	28.6692°N, 77.4538°E
Chennai, India	13.0827°N, 80.2707°E
Bangaluru, India	12.9716°N, 77.5946°E
Chandigarh, India	30.7333°N, 76.7794°E
Jammu, India	32.7266°N, 74.8570°E
Gujarat, India	22.2587°N, 71.1924°E
Hyderabad, India	17.3850°N, 78.4867°E

The database now has 3801 tweets. We track down patterns of use on social networking sites that correspond to certain search terms. We are doing a process of labelling words. The ability to recognise essential phrases is crucial to the success of our investigation. We thus identify the key terms that pertain specifically to the criminal act. The terms "murder," "crime," "encounter," "hit and run," "rape," and "fight" are chosen for the social media crime rate study. For the first spot, 999 tweets are eliminated. On Twitter, the term "battle" is among the most frequently used keywords. Users often search for "crime" in the second location (Table 2).

Table 2. Statistics of tweets collected for the seven corruption metropolises

Location	Murder	Crime	Hit and run	Rape	Encouter	Fight
Jammu	41	43	1	44	78	99
Gujarat	62	50	8	91	37	101
Ghaziabad	117	228	43	222	121	268
Chennai	137	207	10	115	58	190
Bangaluru	170	112	32	111	43	158
Chandigarh	90	52	3	99	27	87
Hyderabad	52	98	12	80	48	156

As the safety of both domestic and foreign visitors is a top priority for the Indian government, these seven areas were chosen for the research. The National Crime Records Bureau found that five of these seven cities.

The most recent crime trends in India's two highest and lowest (Jammu) crime cities are measured using Twitter API as part of the validation of the suggested technique. Throughout the last week (January 23rd–January 30th, 2019), TAGS v6.1 has been used to keep track of crime statistics.

Table 3. Real crime data composed for seven crime cities

Location	Year 2014	Year 2015	Year 2016
Ghaziabad	240475	241920	282171
Jammu	23848	23583	24501
Gujarat	131385	126935	147122
Chennai	193200	187558	179896
Bangaluru	137338	138847	148402
Chandigarh	37162	37983	40007
Hyderabad	106830	106282	108991

2.1.2 Real Crime Data Collection

Each nation's ability to identify and deter crime depends on how well its criminal records are managed. The Indian police force is always trying new things in an effort to make its crime reporting system more effective. After forming a new task force in 1985, the Indian government established the National Crime Records Bureau to centralise and standardise crime statistics throughout the country (NCRB).

The NCRB database is a valuable resource for gathering accurate crime statistics in the targeted areas. We can verify the reliability of this study by comparing it to actual crime statistics that have been obtained by security authorities for the targeted areas. Table 3 displays actual crime statistics for the years 2014, 2015, and 2016 in seven different cities (Table 4).

Table 4. Joint dataset of tweets composed and NCRB crimes

Location	Total crime according to NCRB	Total tweets collected
Jammu	71932	306
Gujarat	405442	349
Bangaluru	424587	626
Chandigarh	115152	358
Ghaziabad	764566	999
Chennai	560654	717
Hyderabad	322103	446

2.2 Proposed Crime Detection Model

In the first stage, information is gathered from a number of users' Tweets using keyword searches. As this procedure generates a flood of tweets, a human filtering procedure is required to go through them and find the gems of information. Around four thousand tweets are collected and screened in this section. The second phase included gathering three years' worth of actual crime data from security authorities in the areas of interest. The final stage involves comparing the reported crimes with the actual ones. A comprehensive description of the model is provided below.

2.2.1 Data Pre-processing

Data pre-processing refers to the steps used to prepare the raw data for input into a neural network. Better results may be achieved if the data is properly structured. The dataset underwent the following preparation procedures:

- Tokenization was performed on all sentences in the dataset. The goal of tokenization is to separate phrases into their component parts, often words.
- A vocabulary is built out of the tokens, and it contains every single word in the dataset.
- A string of words is the input. A tokenizer is developed to transform the string of characters into a numerical series. As a result, each word has its own corresponding numeric value.

2.3 Classification Using Deep Learning

In this part, we provide the proposed model for the crime categorization issue based on the available research. Both the Capsule Neural Network and the Multilayer Perceptron Neural Network play important roles in the model. Whereas the Multilayer Perceptron uses the characteristics retrieved from the text sentences as its input, the Capsule Network uses the transformed sentences as input vectors of a defined length. The final sentence classification is based on the combined output of the two neural networks.

2.3.1 Embedding Layer

This is the model's first layer. This layer's job is to take integer-encoded information and transform it into vectors of a consistent length. Each word in the integer encoded data is represented by a distinct number. The layer is fed random weights and taught to embed the language as a whole. The layer produces dense vector embeddings of a constant size for each word.

2.3.2 Convolutional Layer

This layer is in charge of extracting characteristics from the input phrase at various locations within the text. The same may be said for convolution filters.

2.3.3 Primary Capsule Layer

The purpose of this initial capsule layer in the design is to convert the final result of the convolution layer into a capsule vector representation. This retains the semantic meaning of the words in the statement. This layer has 32-channel capsules that span 8 dimensions. A method known as routing by agreement determines which network layers to ascend to next. When numerous capsules in the current layer cast a vote for a certain capsule in the layer above, the aforementioned process activates that capsule.

2.3.4 Class Capsule Layer

The principal capsule layer's output serves as the layer's intake. Each capsule in the aforementioned layer communicates with the layer underneath it in a specific geographic area. Dynamic routing is the method that bridges this layer with the one below it. At this layer, the routings in the iterative dynamic routing technique are 3, and the capsules have a size of 16. A normalised text feature vector of size equal to the number of features is the network's input. Next, we'll break out how the network's training makes use of characteristics extracted from the data's context.

Sentence Length: This measures the total amount of words in the rumour post, omitting spaces, punctuation, and Hyperlinks.

Some individuals use all capital letters to convey strong emotions; this feature counts the number of words with just capital letters.

This is the number of times negation appears in the criminal report. A set of terms that may be used to convey denial or to symbolise a contradiction are compiled. Words like "never," "isn't," "barely," "no," and "shouldn't" are part of the lexicon.

Most of the time, individuals resort to foul language to express their emotions. Such terms like “moron,” “fuck,” “stupid,” “bastard,” and “bitch” are compiled into a set. The slang forms of these expressions, such as “stfu” and “wtf,” are also included in this compilation. A peculiarity of the rumour post is the quantity of these terms. More often than asking a question or offering assistance, these words are used in response.

2.3.5 The Capsule Network Model

Although several deep neural network-based models have been presented as potential solutions to the issue of crime categorization, there is still room for expansion. In order to improve the precision of the criminal categorization system, this study explores the usage of a Capsule Network. Capsule Network’s first publication demonstrated the model’s superior performance over Convolutional Neural Networks when used to image classification on the MNSIT dataset. By picking up on certain visual cues, a Convolutional Neural Network can reliably identify things. Layers farther into the architecture are responsible for discovering more complex characteristics, such as the eyes or nose (in the case of face identification), whereas the first layers are responsible for recognising basic features like edges. As a result, the best forecast may be made by considering all of these factors together. We may deduce that CNN does not make use of spatial information and that the pooling function is used to link the layers. The fact that the pooling function utilised in Convolution Neural Networks is so effective is a tragedy, according to Geoffrey E. Hinton.

Inverse visuals are one of the goals of a Capsule Neural Network. Because of this, the approach makes an effort to discover the process that produced the desired picture and then replicate it. One of the most important aspects of the Capsule Network is its equivariance. The primary goal is to keep all data about an object’s position and orientation in the network. If the target is rotated slightly, for instance, the activation vectors will shift somewhat as well.

2.3.6 Proposed Crisscross Optimization Algorithm (CCA)

Each iteration of the CCA, a population-based stochastic search method, consists of a horizontal crossover, followed by a vertical crossover. After each round of CCA’s horizontal and vertical crossover and subsequent reselection by the competitive operation, the population is updated twice. Only the most effective solutions will be allowed to continue operating in a competitive environment. There are three reasons why it deserves to be considered excellent.

If you have an issue that spans more than one dimension, you may solve it by splitting the population into hyper cubes and searching the edges of each cube with a lower probability. This improves its capacity to search the whole world.Premature convergence may be prevented with the use of vertical crossover.The competitive process aids in leading to the ideal position and also speeds up the convergence rate.

A. **Horizontal Crossover**

It’s the mathematical equivalent of two people swapping places throughout every dimension. Supposing the offspring of the pth parent is Y(p) and those of the qth parent are Y(q), we predict a horizontal crossover in the Th m dimensions. It is possible to mathematically describe the process of procreation.

$$MS_{hc}(p,m) = k_1.Y(p,m) + (1-k_1).Y(q,m) + l_1.(Y(p,m) - Y(q,m)) \quad (1)$$

$$MS_{hc}(q,m) = k_2.Y(q,m) + (1-k_2).Y(p,m) + l_2.(Y(q,m) - Y(p,m)) \quad (2)$$

where k_1, k_2 and l_1, l_2 are the uniformly distributed values between 0 to 1 and -1 to 1 respectively.

B. **Vertical Crossover**

It's also a crossing in all the dimensions of mathematics between two people. We will suppose that the vertical crossover occurs in the m 1th and m 2nd dimensions for each unique p. It is possible to mathematically describe the process of procreation.

[(MS)]_vc(p, m_1) = k_1.Y(p, m_1) + (1 − k).Y(q, m_2)p ∈ N(1, M)

C. **Competitive Operator**

It's useful for stimulating rivalry between the next generation and its parents. To illustrate, in the case of a horizontal crossing, only the child that performs better than the parent will be evaluated for survival and further consideration.

D. **Crisscross Optimization Algorithm**

1. Initialize the size of the populations (N) and dimensions(M). After that randomly generate population vector '$P_{\mathrm{V_i}}$' and evaluate its function vector '$F_{\mathrm{V_i}}$'.
2. Execution of horizontal crossover with its competitive operator.
   2.1 $B = permute(N)$ (For rearranging dimensions of N) for $p = 1$ to $N/2$.
   2.2 Generate random numbers, $P \in (0, 1)$ and $P_1 = 1$.
       If $P = P_1$ then
   2.3 $no1 = B(2p-1)$ and $no2 = B(2p)$.
       for $j = 1$ to M.
   2.4 Generate random numbers k, $k_2 \in (0, 1)$ and.
       $l_1, l_2 \in (-1, 1)$.
   2.5 Calculate:

$$MS_{hc}(no1,j) = k_1.Y(no1,j) + (1-k_1).Y(no2,j) + l_1.(Y(no1,j) - Y(no2,j)) \quad (4)$$

$$MS_{hc}(no2,j) = k_2.Y(no2,j) + (1-k_2).Y(no1,j) + l_2.(Y(no1,j) - Y(no2,j)) \quad (5)$$

       End for
       End if
       End for
   2.6 New 'P V_2' will be obtained and calculate 'FV_2'
       If $FV_2 > FV_1$ then will obtain best FV and 'PV'
3. Perform vertical crossover with the competitive operator
   3.1 Normalize
   3.2 $B = permute(M)$
       for $p = 1$ to $M/2$.

3.3 Generate random numbers, $P \in (0, 1)$ and $P_2 = 1$
 If $P < P_2$ then
3.4 $no1 = B(2p - 1)$ and $no2 = B(2p)$
 for $j = 1$ to M
3.5 Generate random numbers $k \in (0, 1)$
3.6 Calculate:

$$MS_{vc}(j, no1) = k.Y(j, no1) + (1 - k).Y(j, no2) \tag{6}$$

 End for
 End if
 End for
3.7 Reverse normalizes MS_{vc} and updates PV with the new solution.

3 Results and Discussion

3.1 Measuring the Performance of Model

Recent tweets (obtained through the Twitter API) and real-time tweets (obtained via Twitter Streaming) were classified and labelled independently to evaluate the performance of classifiers with each applicable technique (lexicon-based, machine learning, and hybrid approach). Throughout both the training and testing phases of a model's development, its performance is evaluated using a variety of indicators. The confusion matrix is often used to establish the performance criteria.

A 2×2 truth table matrix, the confusion matrix in this research sums the values of True Pos, True Neg, False Neg, and False. Success is shown by True Pos (True Positive), which indicates the total number of cyberstalking tweets that were successfully identified, while failure is described by True Neg (True Negative). On the other hand, False Pos (False Positive) is a miss-hit that represents the total number of falsely detected cyberstalking tweets, and False Neg (False Negative) is the failure count that illustrates the total number of falsely identified non-cyberstalking tweets. The effectiveness of the cyberstalking detection system was evaluated using standard metrics such as accuracy, precision, f-score, and recall. During the real-time automated identification of tweets, the Area Under the Curve (AUC) was also determined.

3.1.1 Accuracy

Accuracy addresses the complete number of rights predictions anticipated by the classifier. Accuracy can be calculated using Eq. (7).

$$Accuracy = \frac{True\ Pos + True\ Neg}{True\ Pos + False\ Pos + False\ Neg + True\ Neg} \tag{7}$$

3.1.2 Precision

Precision shows the proportion between the true positives and the wide range of various positives. Precision can be calculated using Eq. (8).

$$Precision = \frac{True\ Pos}{True\ Pos + False\ Pos} \tag{8}$$

3.1.3 Recall

Recall describes the sensitivity and measures the proportion of true positive prediction to total positive. Recall can be determined using Eq. (9).

$$Recall = \frac{True\ Pos}{True\ Pos + False\ Neg} \tag{9}$$

3.1.4 F-Score

F-Score measures test accuracy and describe the harmonic average between precision and recall. F-score can be determined using the Eq. (10) (Table 5).

$$FScore = \frac{2Precision \times Recall}{Precision + Recall} \tag{10}$$

Table 5. Analysis of Various Pre-trained CNN Models

Algorithm	Accuracy	Precision	Recall	F-Score
DenseNet	0.918004	0.813725	0.447761	0.379863
ResNet	0.941113	0.426230	0.488060	0.360250
VGGNet	0.957229	0.953846	0.585075	0.310000
AlexNet	0.956454	0.965517	0.567164	0.384987
CapsNet	0.956454	0.636364	0.608955	0.414607
CapsNet C Co	0.96609	0.982456	0.67164	0.585714

All pre-trained models achieved better performance for predicting the crime rate, however the proposed model achieved high performance. The reason is that the hyper-parameters of CapsNet is optimized by CCO model and reaches the better accuracy. For instance, the proposed model achieved 96.60% of accuracy, 98% of precision, 67% of recall and 58% of F-score. But the existing pre-trained models such as DenseNet, ResNet, VGGNet. AlexNet and CapsNet achieved nearly 91% to 95% of accuracy, 63% to 95% of precision, 44% to 60% of recall and 30% to 41% of F-score analysis. Figures 1 and 2 presents the graphical representation of proposed model with existing pre-trained models.

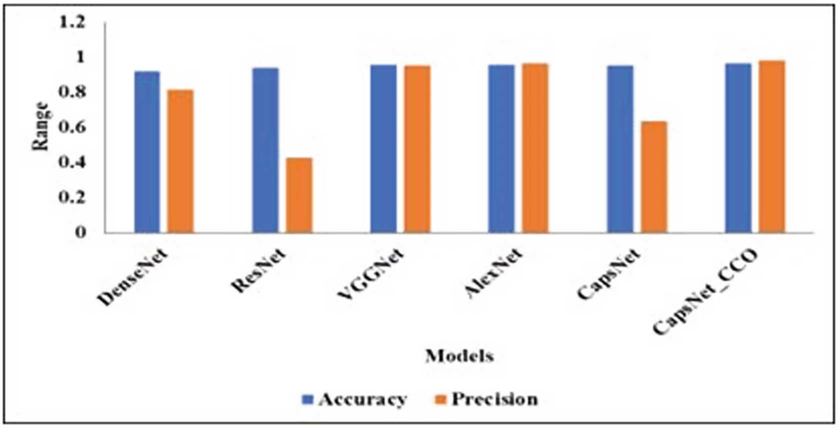

Fig. 1. Analysis of Various pre-trained models

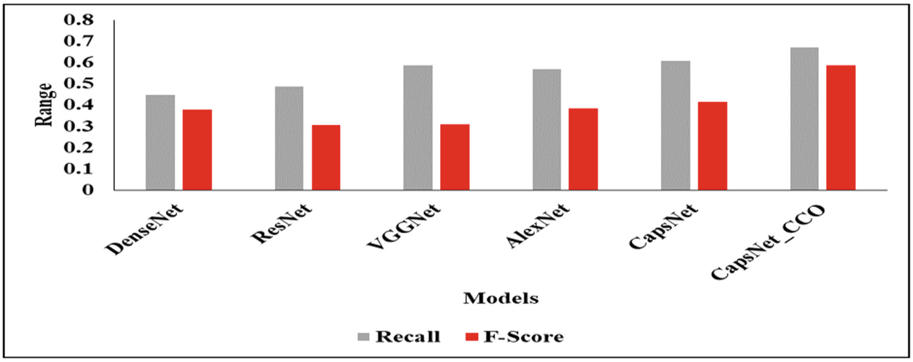

Fig. 2. Comparative analysis of Proposed model with existing techniques

4 Conclusion

The purpose of this research is to analyse crime statistics in real time using information from surveillance systems and public social media platforms. The case study chooses seven key cities from which to carry out the required research. It's common knowledge that many individuals share their thoughts and emotions with their followers all across the globe using the social networking service Twitter. Because of this, we choose to employ Twitter as a social media tool for our study's data collection on criminal activity. Since tweets represent the intents of users and may be detailed and in any format, the process of collecting data via Twitter is a job with a massive processing burden. The first step in our process is to gather the Tweets, then we filter them and lastly we compare them with actual crime statistics. We found that using social media to compare crime rates in different cities was a reliable method. In order to automatically identify criminality on live tweets on Twitter in real-time, a CapsNet model with CCO employing multiple ways on distinct segments was suggested in this article.

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