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An efficient CNN-LSTM model for sentiment detection in #BlackLivesMatter

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ABSTRACT

Imagining things without mixed emotions is next to impossible in today's scenario. Whether it is news or any online movement started on social media applications. One of the social media applications i.e Twitter started a movement known as #BlackLivesMatter. The people from all over the world participated showing mixed reactions, sentiments, and emotions such as trusting the movement, gave negative feedback, felt disgusting, showing anger, etc. In this study, a deep learning classifier Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) is used to detect the sentiments and emotions of the people based on the tweets of the two provinces of the USA (Minnesota and Washington D.C.). The proposed hybrid model is validated over Random Forest, Convolutional Neural Network, Long Short Term Memory, and Bidirectional Long Short Term Memory. It is really surprising to see the results as in both the provinces people showing interest as they are trusting the movement with 48% in Minnesota and 54% in Washington D.C. Our proposed model CNN-LSTM is 94% accurate in detecting the various sentiments based on the hyper-parameters such as epoch, filter size, pooling, activation function, dropout, stride, padding, and number of filters.

1. Introduction

With the inception of social media data across the globe, problems related to the intensity of data also expands. It becomes challenging for the software tools and technologies to visualize, store, manage, and analyze due to the gradual growth and accessibility of digital data. The huge rise in the volume of data, diverse variety in data, velocity of the incoming or outgoing data arethe basic reasons for the escalation of social media data (Chen & Lin, 2014). Though a fact that social media connects people all around the world, a big knowledge is required for the task extraction. The important information is being pulled out from the raw data available and then extracting knowledge out of the information is yet a big problem to solve. Additionally, storage of data and access to data also are big challenges. The collection of data from different storage from different databases for different shots but is also another challenge to deal with. As per experts, the relational database and database management system are the standard choice supported by the developers (Vial, 2018). There exists SQL to handle use-cases with the object-oriented databases dealing with social media platforms such as Twitter, Facebook, Google, Yahoo, etc. Twitter, one of the social media platforms gaining a lot of attention from people's everyday lives. The exemplification of these platforms needs to be dealt with such as Machine Learning, Natural Language Processing, etc (Hanna, Rohm, & Crittenden, 2011). Machine and Deep Learning techniques along with advances taking place in computing are responsible to take out the information from the data available. As a result, deep learning is a powerful technique in dealing with social media analytics. The approach to reach the topic in many ways from pure ordered based to the more serious deep learning's neural network. To train the model using deep learning classifier's algorithms the relevant tweets can be labeled based on emotional polarity (Nemes & Kiss, 2021). As a result of the study of global movements and individual's impact on that social data is a valuable tool for conducting these types of movements. #BlackLivesMatters formed in 2013 in the United States indicated the unjust killings by police of the black people. It was the online movement started. The reaction to this is positive as well as negative. Black Lives Matter is the protest against

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the brutal police incidents and also racist violence against African–American people. This study attempts to work on the data collected from the Kaggle. As the advancements can be seen in the deep learning text-based approach such as BERT in which based on tweets of the people the sentiments attached to the texts can be classified (Devlin, Chang, Lee, & Toutanova, 2018). With the interactive discussion and communication among virtual networks and communities, web-based technologies such as social media analytics came into the picture. All the data is being generated from the online interaction among the users such as comments in the form of text, audio, and video clips. In general, there exist some service-specific social media profiles that can be controlled by the government itself (Pang & Lee, 2008). Different social media platforms can help the different types of users to connect the people having similar interests such as Facebook, Twitter, Linked In, etc. The data can be collected, evaluated, and analyzed as per the requirement. The next step involves the different steps for the real-time customer experiences such as updating of data, data expanding, and lastly, data evolving. Therefore the motivation behind this is collecting the emotions of the people from the two provinces of the country USA for this social media online violent movement and displayed the results of sentiments of two states of USA namely Minnesota and Washington D.C.

The key contributions of the following paper are as follows:

- In this study data is collected from Kaggle, the two provinces of the USA for the social media movement #BlackLivesMatter.
- The proposed model of deep learning classifier Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) is applied for the sentiment analysis for #BlackLivesMatter.
- The results of two provinces of the USA that is Minnesota and Washington D.C are displayed.
- The comparative analysis of different deep learning classifiers with the proposed model validates the model of this article.

The remaining part of this paper includes the deep learning models for sentiment analysis covered in Section 2, Section 3 comprises of Preliminaries, next Section 4 includes Proposed architecture and Methodology, Results and Analysis in Section 5 concluded with Section 6 Conclusion.

2. Related work

2.1. Sentiment analysis

There exist many traditional methods for sentiment analysis that makes the use of supervised learning methods as a clustering or classification module (Chauhan et al., 2020). The exploitation of various types of models such as a bag of words and n-gram for the classification of user-generated sentiment-bearing texts (Liu, 2015). The above-discussed models for addressing the bag of words problem by including and ignoring word order and syntactic structure (Zhao, Peng, Eger, Cambria, & Yang, 2019). Having a drawback of the n-gram model's features the several types of feature selection methods have been used (Duric & Song, 2012). A variety of classification methods for sentiment analysis exists for detecting the emotions and sentiment of the user from the type of text a user is typing such as Support Vector Machines, Naïve Bayes, Artificial Neural Networks gained a lot of attention. But there exist many problems with the following methods as the requirement of a large amount of data for the training process makes the process slow (Abbasi, France, Zhang, & Chen, 2010).

2.2. Deep learning models for sentiment analysis

Natural Language Processing attracted a lot of research domains in which the text representations can be analyzed and explored. Several methods have been proposed in (Nobata, Tetreault, Thomas, Mehdad, & Chang, 2016) for speech detection from the past years different from the traditional learning methods to modern deep learning methods. The survey (Taylor, Peignon, & Chen, 2017) uses the Twitter data for the identification of online speech using the Neural Embedding Model which can find the similarity between the words. Also helps to learn the out of dictionary words containing some special and code words. The survey (Malmasi & Zampieri, 2017) which is having Twitter-related posts used the content and speech analysis using Support Vector Machine (SVM) classifier. There exist three groups that extracted the features and achieves the best accuracy. The survey (Badjatiya, Gupta, Gupta, & Varma, 2017) uses various deep learning classifiers to detect racism and sexism. It uses Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM) and achieved better results. The survey (Bhargava, Sharma, & Sharma, 2016) makes the use of Recurrent Neural Network one of the deep learning classifiers which use a lot of strategies to handle contextual and emotion-related problems. In the survey (Sailunaz & Alhajj, 2019) Machine Learning approach Naïve Bayes algorithm gave the best result for sentiment and emotion detection. In the survey (Zhang & Wallace, 2015) authors dealt with the classification of textual sentiment problem where a CNN model has been proposed having 2 convolutional layers, pooling layer, embedding, and fully connected layers and are compared to the other classifiers. Mainly consecutive convolutional layers are used for dealing with the problem of the sentences dealing with the long text. The survey (Mao, Chang, Shi, Li, & Shi, 2019) made use of sentiment-aware word embedding for the improvement of emotional analysis. The deep learning classifier BiLSTM had been used to analyze the emotions and concluded the result. The survey (Jabreel & Moreno, 2019) addresses the multi-class emotion analysis in tweets by using the deep learning classifiers where the use of Recurrent Neural Networks (RNNs) with a classification module that uses activation function ReLU with the two feed-forward layers to achieve the desired results. The variants of LSTM and LSTM alone can be used in various applications for the problem of sentiment analysis and survey (Young, Hazarika, Poria, & Cambria, 2018) came up with the cached LSTM to learn various semantic features including local and global but in long text. The survey (Ma, Han, & Wang, 2020) worked on the optimization models results in prediction-based portfolio using deep neural networks. The survey (Oliver, 2020) used the LSTM network for comparing the models of classic time series. There exist various Natural Language Processing tasks for the achievement of state-of-art results, a powerful transformer-based model has been proposed known as Bidirectional Encoder Representations from Transformers (BERT). The bidirectional transformers are used to pre-train the word presentation model. The working of BERT is to predict the next sentence and learns the embedding having large context. The two parameters are responsible for the performance analysis such as BERTbase and BERTlarge (Khan et al., 2021). For the tuning of BERT for detecting hate speech by using the proposed annotated data and a pool of labeled training examples. A custom classification head is used on the top of both models for the fine-tuning of both BERTbase and BERTlarge.BERTbase uses a 12-layered transformer, 12 attention heads, and 110 million parameters. On the other hand, BERTlarge uses a 24-layered transformer, 16 attention heads, and 340 million parameters. In the present work, the sentiment and emotion analysis based on tweets on Twitter of two provinces of the USA is taking place.

3. Preliminaries

This section contains the basic overview of how the proposed model CNN-LSTM is to be built for the emotion or sentiment analysis. The following subsections have the CNN and LSTM details. Specifically, CNN and LSTM are described as follows.

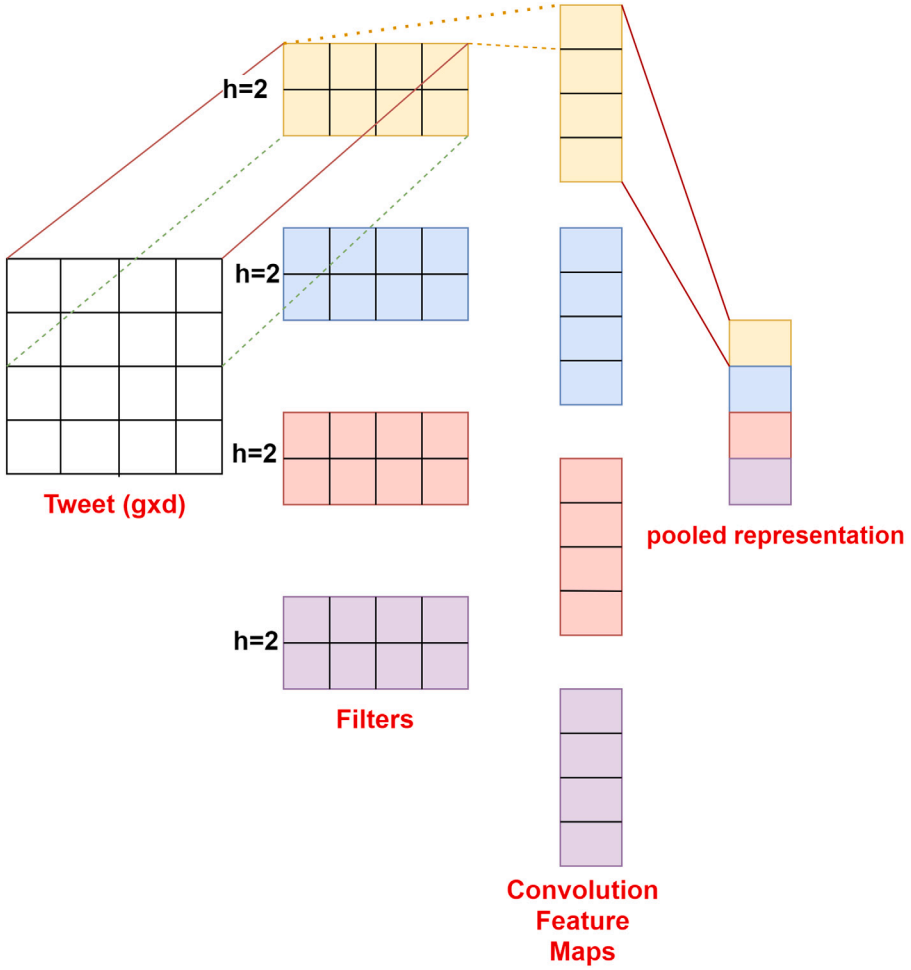


Fig. 1. CNN for feature extraction. The input is a sequence of d-dimension word embeddings (e = 4), four filters for h = 2 are applied to the embeddings and four feature maps are generated. The max-pooling is used to generate a pooled vector of size 4.

3.1. Convolutional neural network

The Convolutional Neural Network contains the various convolution layers and is used in various applications such as Natural Language Processing both for local and global extraction of features. In Convolution Neural Network, on input features, an operation like convolution is performed with the help of linear filters. For the application of a convolution neural network on the sentence E with e words first, and embedding vector of size o is created. Then a filter L of size o x h is applied to the sub-matrices of the input feature matrix. This results in feature map of R= r_0, r_1 ..... r_{e-h} as follows (Jabreel & Moreno, 2019):

$$m_r = L \bullet E_{i:i+h-1} \tag{1}$$

where i = 0, 1, . . . , e–h an sub-matrix of E from row i to j. The feature map's dimensions are reduced by feeding them into the pooling layer. The common strategy for pooling is max-pooling used to opt for the most important feature b of the map as follows:

$$b = max[m[i]] \tag{2}$$

where, 0 ≤ i ≤ s − h. The concatenation of pooling layers with output results in a pooled feature vector also used as fully connected networks input as shown in Fig. 1.

3.2. Attention model

The different weights have been assigned to words of the text to analyze the sentiment, for this the attention model is used. All the hidden states h use a weighted combination so that different weights are assigned to different words in a sentence in (3) and (4) also as shown in Fig. 2 where h are the hidden states and v is a trainable parameter.

$$\alpha t = \frac{exp(v * h)}{\sum_t exp(v * h)} \tag{3}$$

$$S_{A_w} = \sum_t \alpha_t h_t \tag{4}$$

3.3. Long short term memory

A special type of deep learning classifier's Recurrent Neural Network (RNN) is made in such a way that can be able to handle the vanishing problems. RNN handles the time-series sequential problems. Long Short Term Memory (LSTM) is the type of RNN which based on the current input the output is being generated and then the previous step output is also sent to the next time step's output. Every unit of LSTM has a memory cell C_k in which the state is preserved in random time intervals also having three types of non-linear gates having an input gate I_k, output gate o_k, and the forget gate f_k. The information flow can be regulated in and out of the memory cell. The LSTM memory cell is shown in Fig. 3.

Suppose $\sigma(.)$, relu(.), and $\odot$ are the sigmoid functions have taken element-wise, also hyperbolic rectified linear activation function and product. The inputs x_k and h_k and the hidden state vector k. P and Q show the weight matrices of cells or gates for input x_k and the hidden state h_k and b is known as bias vector. The information that needs to

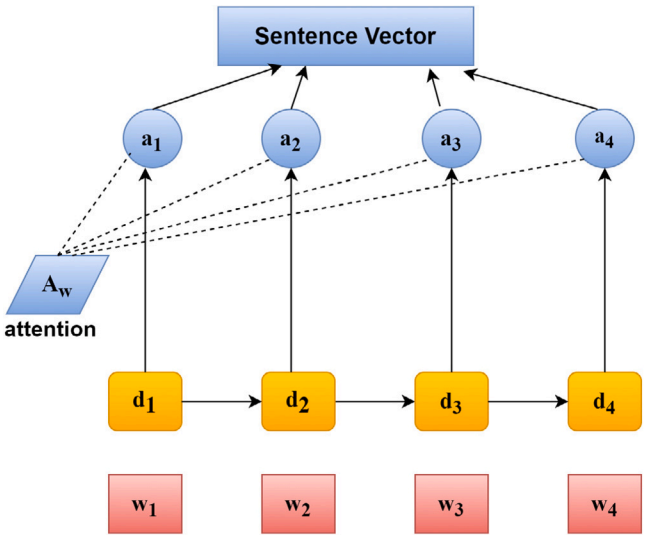


Fig. 2. Attention model.

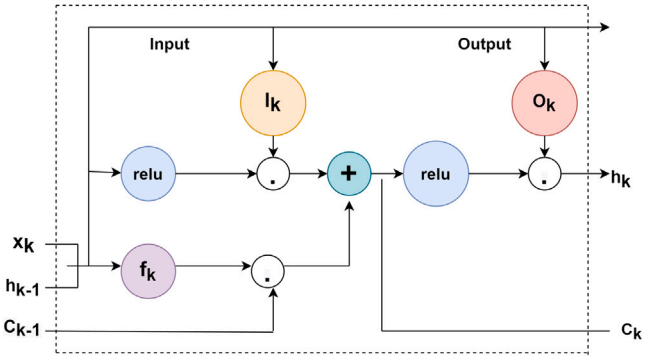


Fig. 3. LSTM memory cell.

be forgotten is the decision taken by the forget gate according to the following equation (Young et al., 2018).

$$f_k = \sigma(Q_f h_{k-1} + P_f x_k + b_f), \tag{5}$$

The new information to be stored by computing i_k is decided by the input gate and combining the following equation.

$$c_k = \sigma f_k c_{k-1} + i_k, \tag{6}$$

The decision of which part of the cell will take participate in the output is decided by the output gate.

$$o_k = \sigma(Q_o h_{k-1} + P_o x_k + bo), \tag{7}$$

$$h_k = o_k \bigodot (c_k), \tag{8}$$

As h is used to capture the context results in the temporary flow of information and also for the better learning of model.

4. Proposed architecture and methodology

This section contains the steps for loading the dataset. The description of each is given below having the following steps namely the data collection, preprocessing of data, data analytics, sentiment analysis, data annotation, and then the desired results take place.

4.1. Proposed model CNN-LSTM for sentiment analysis

Deep Learning Classifier Convolutional Neural Network and Long Short Term Memory the sequence of input is fed to ConvNets used in various applications one of them is Computer Vision (Srinivas et al., 2016). For applications related to Natural Language Processing(NLP) gaining a lot of attention in the research domain and also so many tasks related to NLP are being performed (Dos Santos & Gatti, 2014). The first step is ConvNets responsible for the extraction and classification of features. This deep learning classifier has advantages in many fields and also in text analytics (Zhang, Zhao, & LeCun, 2015). The convolutional network layer consists of so many convolutions and pooling layers that can be used for the hierarchical representation of sequential input data. Then the use of many hyper-parameters for tuning purposes and to obtain the output of the desired choice the use of forwarding and backpropagation is mandatory. The Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) for sentiment analysis is shown in Figs. 4 and 5.

As discussed above the mandatory two layers are convolutions and pooling layer, the convolutional layer is the heart component of the framework in which multiple numbers of convolutions are being performed using the kernel function so that the relative feature maps can be obtained. The next step is the use of the activation function which is either ReLU or tanh after obtaining the feature maps from the convolution layer. This is an important step as the requirement of the neural network should be powerful and also non-linear (Zhang et al., 2015). The major point to be noted is that the input size whether it is text, speech or image should always greater than that of the kernel size so that it can be perfectly fit into the input space. The feature map size and kernel size are directly proportional to each other. Also, the use of padding is responsible for increasing or re-sizing the feature map to that the size of the input. This could help in maintaining the feature map size and also protects the feature map's getting narrow at each layer present in the convolutional neural network. One more parameter the network is relied upon which is responsible for the movement of input data by specifying the number of steps known as stride helps in moving the kernel around the input and by default is set to 1. The next layer that comes into the picture is the pooling layer which directly takes care of the data dimensionality which also handles the overfitting issues and reducing the data dimensionality by decreasing the training time. The popularly known layer of pooling layer is the Max-Pooling layer where the sliding of the window takes place and it uses the layer having maximum turnouts. The pooling layer generates the output which can be converted into a one-dimensional array then can be sent to the fully connected layers in which the training model process takes place by using both forward and backward propagation having a key component which is the gradient descent method. Then the addition of parameter dropout in the next step is used for the process of regularization in the training phase (Zhang et al., 2015).

The accuracy can be boosted up if a certain number of neurons can be dropped out inside the network based on the probabilistic decision. The neurons dropped out prior can be made active if the next set of neurons can be dropped off. This operation cannot be applied anywhere, it can only be applied to the input as well as the hidden layers to obtain the desired output. The output from the dropout is fed to LSTM for giving the best results in a sequence of inputs. For better representation of the input, the use of some pre-trained word vectors among the hyper-parameters take place.

4.2. Methodology

Following steps are followed to implement the proposed architecture where data is to be collected first then that collected data is to be preprocessed then data analytics takes place based on which sentiment analysis takes place as shown in Fig. 6. The data will be annotated categorize into hateful (Anger, Fear, Disgust) and non-hateful (Trust, Surprise, Anticipation) shown in Table 1.

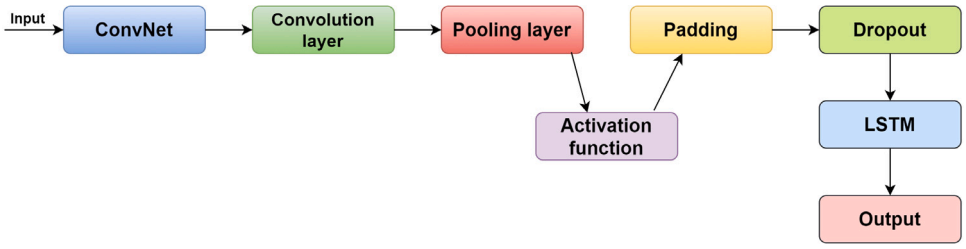


Fig. 4. CNN-LSTM for sentiment analysis.

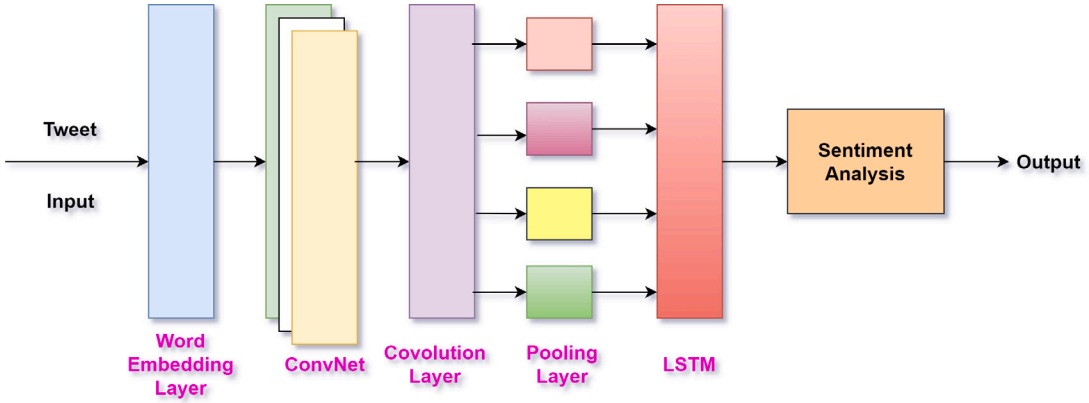


Fig. 5. Proposed CNN-LSTM for sentiment analysis.

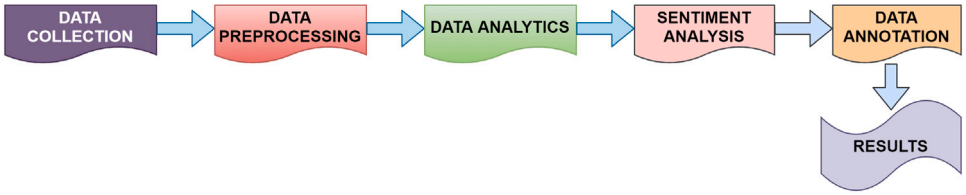


Fig. 6. Steps to load data.

4.2.1. Data collection

A Python library is Tweepy3 for the collection of Twitter data and also for accessing the Twitter Application Programming Interface. Several samples were collected and on an average, per day basis the data will be collected. The 7,346,842 English tweets can be taken for the dataset, the number of users selected based on the followers. For extraction of the tweets related to the Black Lives Matter movement, the use of hashtags in a sentence a group of keywords being built which is being accepted in lowercase as well as in uppercase. There also exist some keywords such as Black Lives Matter, Change The System, and many more that were being collected from speech-specific tweets. The final number of tweets was then collected.

4.2.2. Data preprocessing

The data is obtained and exported in readable format therefore before the execution process the data is to be preprocessed. The proper format of data is taken then text summarization and sentiment analysis are to be done. There also exist root-based words that provide sentiments behind the reviews and are being used for the summarization of the text. The segmentation is being applied first then the long strings of texts are split into paragraphs. The individual words are being taken and performed the next step of stemming obtaining the root word. The unnecessary words are being removed which does not contribute to the sentiment of reviews. The next step is noise removal where the removal of unwanted tags takes place. The use of library NLTK enables the user to work for different applications. Tweets are firstly preprocessed and converted into lowercase. Some unwanted or unnecessary keywords such as the username, link, retweet must be removed. Also, the python module NLTK is used for the processing of text where English stopwords are being removed and lemma tweets are being performed (Badjatiya et al., 2017). The collection of text documents can be converted into a vector of tokens can be done by Scikit-learn's Count Vectorizer. This module is used to tokenize the tweet-related text where a known words vocabulary is built and also the features will be extracted.

4.2.3. Data analytics

In real life, the data based on text applications gained a lot of performance till now. The comparison of image and speech fields works on several applications such as Face recognition, Speech recognition, Emotion detection with that of the signals coming from the speech concludes the results very fast. There exists a problem with the classification of text which rotates around the text-only, the result of holographs, metaphors, and many other words result in the ambiguous data thus making the problem, much more complicated (Bhargava et al., 2016). The accuracy of the system can be obtained by the way the system should be trained but with a restriction of not being used in real-world applications. The feel of emotions can be interpreted by the signal obtaining from speech as the amplitude and frequency vary. The

same could be the procedure for texts, the words full of sarcasm and irony make the problem of emotion detection even more problematic. Therefore, the above-mentioned points discuss the working of data related to text along with the attainment of accuracy for a standardized model. Several applications are being built using text data only and also many text-related data are generated on daily basis. The next word's prediction at the time of google search or sending the text messages, spelling and grammar checking, at the time of using email correcting the wrong and misspelled words, classification of the document in which the same type of documents can be clustered together just like making folders for anything indistinguishable languages, authors can be identified based on a document which does not contain the name of the document, profile of the particular author containing the age, language, gender with many more characteristics, translation of one language to another language on a machine, retrieval of information from legal documents, extraction of phrase, detection of any paraphrase, sentiment analysis, with many more applications which are yet to come (Nobata et al., 2016).

4.2.4. Sentiment analysis

As per the name sentiment analysis this will try to come out the emotions that exist behind the text data. It includes various types of emotional feelings such as trust, anger, happiness, disgust, fear, the feeling of joy, etc. There exist three levels of sentiment analysis such as sentence, document, and feature level. Digital text containing emotions can be interpreted the humans by just knowing the people or users' state of mind behind the context of the text. It is even more problematic if deal with humans. But in the case of machines, the concept is different as machines can hardly understand the emotions, feelings, sentiments, and context of an individual. The digitalized technologies attracted the interest of the people as the time changes from reading newspapers to buying things and giving reviews, comments, and feedback for the same. There are various e-commercial sites such as Amazon, Flipkart, Cilory, etc. in which a person can be in a state of liking and buying a product but cannot be able to judge the quality of the same just by looking to the comment section. In the same way when it comes to text messaging to our loved people or if it is about updating the status on social media it is difficult to know or judge the feelings or sentiments of the individual (Pang & Lee, 2008). The above discussed comes under the use of emotions in digital text data which are not only can detect emotions but also helps in a variety of fields such as Cybersecurity, Law and Order, Business Statistics, Marketing analysis, etc. In the business field, it came out to be an important module as the organization's profit deals with the satisfaction of the customer. Most of the cases in sentiment analysis are turned out to be problematic because of the unstructured data. The reason behind this is whatever message is to be typed on social media, any comment or review, or feedback on any product does not have any type of specific format and language. The comments, messages, tweets, feedback, and reviews can be in any language whether it will be the mother tongue or any global language or it could be a combination of both. To be more precise and clear let us take the example of countries like India where a lot of languages are being used. For expressing their feelings, views, and emotions people in India uses a lot of languages such as Hindi, Marathi, Tamil, Malayalam, etc. To convey messages or comments the combination of languages or dialects of languages results in code mixed data. The complication arises as to the structure of both data and regular language are different (Taylor et al., 2017). Apart from different languages, the use of emojis and hashtags which are in trend since the late 90s on social media has left an impact specifically which automatically came up with the complexity in the text structure and also emojis present with them.

Table 1
Label and ID of class.

Hateful and non hateful	*Name*	*Annotation class*
Non hateful	Trust	0
Non hateful	Surprise	1
Hateful	Anger	2
Non hateful	Anticipation	3
Hateful	Fear	4
Hateful	Disgust	5

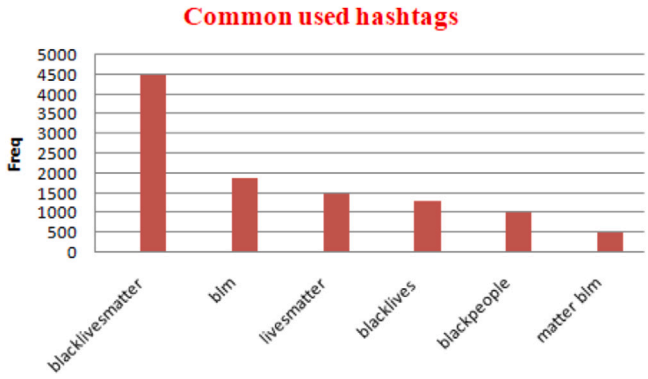


Fig. 7. Common used hashtags.

4.2.5. Data annotation

After gathering the data, it is to be annotated. As in Table 1, there exist six emotions three are from the non-hateful category (Trust, Surprise, and Anticipation and three are from the hateful category (Anger, Fear, and Disgust). Based on the number of times the tweets having hate and non-hate the categories were chosen.

- Non-Hateful Text: This particular category contains tweets having positive, neutral data, trust, also containing those tweets or information different from the above category and that does not harm the emotions and sentiments of an individual, group of people, culture, etc. The data annotation is based on the results taken by the five people annotators proficient in the English language helps in detecting both hate and non-hate speech for Black Lives Matter. The gathered dataset is annotated by 5 annotators whose age is between 23–28 out of this 2 are undergraduate students and 3 are Masters students. The dataset consists of tweets where two annotators out of three have fully based agreement. Finally, the result is based on a full agreement between the two annotators. If the final process has no full agreement between the remaining annotators the tweets will be deleted. For experimenting the data gathered is enough. As a result, we are left with 2031 hate speech and 5123 non-hate speech. There exist some commonly used hashtags for BlackLivesMatter refer to Fig. 7.
- Hateful Text: The following category is having those tweets containing emotions full of hate, anger, and disgust also focusing or attacking the racist groups and making people down based on religion, gender, age, or sexual orientation.

5. Results and analysis

The snapping of data into 20 training sets and 80 testing sets is then the major step in the training of the Neural Network classifier. At the time of training and embedding, the layer is created first. The embedding layer is mandatory as it can able to solve the out-of-vocabulary problem and can also find similar character dimensions. In the next step conv1d layer created uses kernel size 3 this layer meaning the training data input contains rows that are convoluted with each other and uses a 3 filter. For maximum value extraction, max-pooling

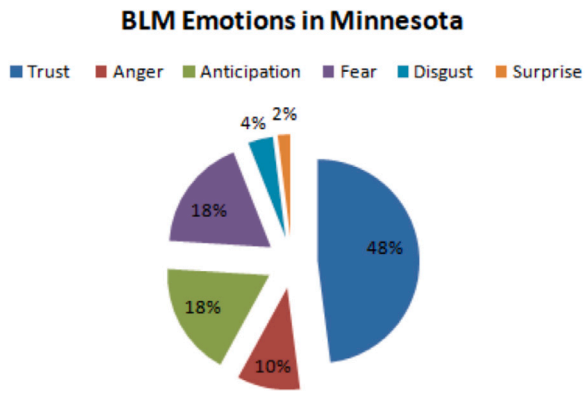


Fig. 8. Sentiment analysis of Minnesota.

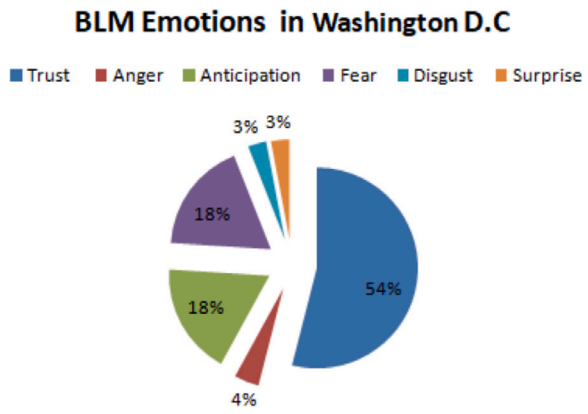


Fig. 9. Sentiment analysis of Washington D.C.

is used having a softmax activation function where the dense layer has a dropout of 0.5 to avoid overfitting. The input which is a combination of words using a hashtag is fed to the ConvNet then it is fed to one of the layers namely the convolutional layer then it is fed to the pooling layer in which output is generated in the form of the one-dimensional array then fed to softmax activation function use of padding takes place after that use of dropout for the regularization of training model, then use of max-pooling is used to obtain the desired output.

5.1. Experimental analysis

The hyper-parameters are optimized, discussion of which is discussed above after that the training of the model takes place using final parameters such as epoch is 18, the filter size is taken to be 3, pooling is maximum as it will extract the maximum value with softmax activation function for the final classification process having 0.5 dropouts, the stride is 1, valid padding and number of filters to be taken are 600 so that the final emotion sentiment can be analyzed.

Parameter	Value
epoch	18
filter size	3
pooling	softmax
activation	ReLU
dropout	0.5
stride	1
padding	valid
number of filters	600

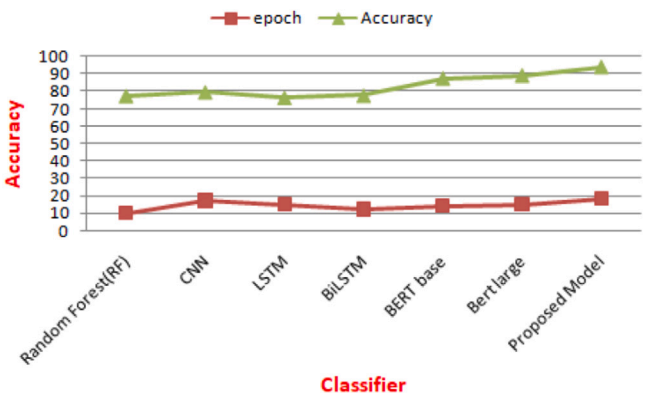


Fig. 10. Comparison of various deep learning classifiers.

After experimenting with the Sentiment Analysis of two states of USA (Minnesota and Washington D.C) having different emotions such as Trust, Anger, Anticipation, Fear, Disgust, and Surprise. The sentiment analysis as discussed above the combination of various feelings such as the feeling of trust, anger, anticipation, fear, disgust, and surprise of two United States provinces such as Minnesota is shown in Fig. 8 and Washington D.C is shown in Fig. 9. In both the above-mentioned figures people tend to tweet positive content to encourage each other also showing respect to the leaders and the social media algorithm is also biased to promote the positive emotional content than the negative content. Also, the comparison of different deep learning classifiers is shown in Table 2 and Fig. 10.

5.2. Evaluation criteria

The performance of the model is based on the efficiency and accuracy of the working of model. There are some parameters exists on which efficiency depends upon such as confusion matrix, precision, recall and accuracy. The confusion matrix with precision and recall is as shown in Table 3.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$Recall = \frac{TP}{TP + TN} \tag{10}$$

$$Precision = \frac{TP}{TP + FN} \tag{11}$$

where, TP = True positive class prediction, TN = True Negative class prediction, FP = False positive class prediction, FN = False negative class prediction.

6. Conclusion

In the following study, one of the online movements #BlackLivesMatter started all over the world by using social media applications such as Twitter. A lot of people participated in this movement, tweets on a social media application Twitter supporting, arguing, showing anger, anticipating the movement, also showing fear, surprised from the movement showing different emotions and sentiments regarding the movement. An efficient CNN-LSTM model has been proposed to detect the various emotions on this particular movement for two provinces of the USA i.e Minnesota and Washington D.C. It is really surprising to see the results as in both the provinces people showing interest as they are trusting the movement with 48% in Minnesota and 54% in Washington D.C. Our proposed model CNN-LSTM is 94% accurate in detecting the various sentiments. Experimenting the same with the remaining deep learning classifiers to improve accuracy by improving the parameters is a further area of investigation.

Table 2
Accuracy of deep learning classifiers.

Classifiers	Technique with Frequent Words used	Epoch	Accuracy
Random forest	Prediction, Decision trees, Sentiment analysis	10	77.35%
CNN	Softmax, Adam optimizer, Sentiment analysis	17	79.46%
LSTM	Dense vector, Sparse features, Sentiment analysis	15	76.21%
BiLSTM	Sequence tagging, Sigmoid, Activation function, Sentiment analysis	12	77.58%
BERT base	Classification, dropout	14	87.45%
BERT large	Classification, dropout, Sequential, Sentiment analysis	15	89.13%
Proposed model	Activation function, ReLU, Dropout, Sentiment analysis, LSTM	18	94%

Table 3
Confusion matrix.

Emotions	Anger	Surprise	Trust	Anticipation	Fear	Disgust	Prec	Rec
Anger	70.3	1.6	1.6	6.2	6.2	4.7	61.63	68.79
Surprise	17.5	12.5	2.5	17.5	35.5	1.0	64.74	70.28
Trust	26.1	2.2	2.2	8.7	26.1	28.3	56.75	36.76
Anticipation	1.6	0	0	87.3	6.3	3.2	56.44	57.23
Fear	1.6	3.3	0	13.1	27.9	44.3	73.38	69.19
Disgust	15.2	0	0	8.7	37.0	32.6	82.24	74.08

CRediT authorship contribution statement

Ankita: Conceptualization, Methodology, Resources, Writing – original draft. **Shalli Rani:** Conceptualization, Methodology, Resources, Writing – original draft. **Ali Kashif Bashir:** Validation, Writing – original draft. **Adi Alhudhaif:** Validation, Formal analysis. **Deepika Koundal:** Validation, Formal analysis, Data curation. **Emine Selda Gunduz:** Validation, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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