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Identifying Radical Activity on Social Digital Platform: A Machine Learning Approach

Vandna Batra[*] and Suresh Kumar

Department of Computer Science & Engineering, Manav Rachna International Institute of Research and Studies, Faridabad, India

([*]Corresponding author's e-mail: vandana.fet@mriu.edu.in)

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Abstract

The social media in digital form over internet is getting popularity in recent years. This digital platform is being used by many to share their thought or opinion. Though these social media had given results too many good causes, there are some users are present on these platforms for radical activities. In this paper, the tweets form the digital social platform twitter is taken for analysis based on radical keywords. The data is collected in form of tweets are analyzed using different machine learning algorithms and a comparative analysis is done. The proposed work concludes the best machine learning algorithms for analysis of such data and the new words came in light for the collected dataset. The deep learning model are also implemented and tested for sentimental analysis.

Keywords: Sentimental analysis, Radical activity, Machine learning, Deep learning

Introduction

Digital social media is exponentially growing with the growth of the digital network for a few decades. There are many social media platforms over the internet where people share their opinion and thoughts. Users over such social media develop a strong bond among themselves by sharing their opinion in form of images, comments, text messages, etc. Sharing of one's feelings, opinions, and thought are very common on such social media platforms.

One of the popular social media, Twitter is the fast-growing platform over the internet. The short messages created, updated, and posted on this platform are known as tweets. These tweets sometimes are a reason to influence many people. Even journalists of various media also keep the track of the important tweets on this platform and even retweets it to show its importance [1].

The study of these tweets in a scientific way is known as sentiment analysis. Sentiment analysis is the way of knowing the polarity of the text in tweets, which leads to identifying the tweet having a negative or positive sentiment [2].

The proposed work is about the sentimental analysis of the dataset extracted from Twitter using radical words. The different machine learning algorithm is used to implement the model based on its advantages and disadvantages. A comparative study is done among all implemented models and finally concluding a model with best accuracy.

Literature review

In the recent growing social online network, it has become a support to the terrorist groups like ISIS [3]. The possibility of such radical activity over an online platform has attracted many researchers to find their existence on social media. The concern is to automatically find their existence and take corrective measures. Ashcroft *et al.* [4] has used a machine learning model to analyze tweets and detect the supporters of terrorist groups like ISIS. The tweets based on the keywords ISIS were taken for making the model. All the tweets taken were in the English language. Stylometric features, temporal features, and sentiment features were considered to make classes. Gupta *et al.* [5] proposed an automated system to classify the tweets as radical or not. The use of machine learning algorithms SVM, AdaBoost, Random Forest, and Naïve Bayes with different parameters were used. The characteristics of the terrorism-related tweets on Twitter social media for the pre-detection of terrorism activity was proposed by the author in [6]. The suspended account as well as the non-suspended account was used to gather tweet data. Agarwal

and Sureka [7] has used a single class SVM and KNN algorithm detecting the negative emotions, presence of war or negative emotion in tweets. Their proposed approach has an F-score of 0.6 for KNN and 0.83 for the SVM classifier. Rowe and Saif [8] studies the activity of users before, after, and during any ISIS event. To exhibit a radicalization behavior a term-based approach was used. The proposed approach was not able to properly handle lexical ambiguity. Nouh *et al.* [9] had collected a dataset from social media to evidence radicalization activity over the internet. A psychological nature and derived linguistic from propaganda by the specific group for involving people in such activity. Ashcroft *et al.* [10] had proposed a model to dynamically identify radical activity by using a machine learning approach. The proposed model is trained by the tweets dataset. The tweets were collected by the keyword "jihadists". Features were dependent on the dataset and it came as a drawback of their model. Lara-Cabrera *et al.* [11] had set indicators for the radical activity. Dataset is prepared using tweets based on sham sympathizers and the state of Iraq. They concluded with a strong relationship between the parameter assigned by the model and indicators.

The study shows that there is very less work done for radical activity on the social digital platform. There is the scope of improving detection of such activity in advance by continuously monitoring these platforms using different advanced machine learning algorithms and also most of the authors have worked upon some common words for data collection. In the proposed work, analysis has been done using some advanced machine learning algorithms; finding some out of dictionary words that are directly related to the radicalized words. Accuracy is obtained by different learning algorithms and has concluded 1 which gives the best results.

Data collection and pre-processing

The dataset has been collected from Twitter. The tweets are searched based on the keywords. The dataset is collected in 3 parts based on the different keywords. A dataset (Dataset1) of 10,355 tweets is fetched with the keyword "TabligiJamaat". **Figure 1** shows a portion of the dataset. The keywords are such taken that can define radicalization in society. In the proposed work the radical dataset is taken for the sentiment analysis using different machine learning algorithms.

```
array(['news tabligijamaat show muslims positive light media',
       'guts tell directly tabligijamaat rather telling single sour
ce something',
       'tabligijamaatmuslims r revealing source people right know b
ette',
       'plz correct anuragmuskaan trump didnot threaten indialuteyn
s media twisted tak',
       'right totally ban tabligijamaat became threat nation'],   dt
ype=object)
```

Figure 1 Dataset based on keyword "TabligiJamaat" (5 tweets).

Second, a dataset (Dataset 2) of 25,547 tweets based on the keyword "Al Qaeda" is fetched from Twitter. **Figure 2** shows a portion of the dataset. The third dataset (Dataset 3) of 15,825 tweets based on the keyword "Corona Disease" is fetched. **Figure 3** shows a portion of the dataset.

For natural language processing in python, TextBlob library is used. Text Blob made extensive use of the Natural Language Toolkit (NLTK) to accomplish its objectives. NLTK is a library that enables users to easily access a large number of lexical tools and perform categorization, sorting, and a variety of other activities. In the proposed work, Text Blob is used to decide the polarity of a tweet. The polarity obtained by Text Blob is in the range of −1 to 1. −1 polarity is treated as negative tweets, whereas 1 is for positive tweets. If the polarity is 0, then the tweet is treated as neutral.

After removing neutral tweets from the dataset, the number of positive and negative tweets is shown in **Table 1**.

```
array(['al qaeda linked ansarghazwatul hind aghkashmir releases propag
anda poster photo jihad',
       'rt al qaeda linked ansarghazwatul hind aghkashmir releases p
ropaganda poster photo jihadist us',
       'rt thought al qaedaisis threat much evidence suggest china o
rchestrated pandemic de',
       'chandsardaaravinash kind',
       'rt top indian editors treating tj discussing isis al qaeda c
hoice words tj chief'],
dtype=object)
```

Figure 2 Dataset based on keyword “Al qaeda” (5 tweets).

```
array(['rt women girlsinict day schools closed due covid19 pandemi
c many take virtual classes others especial',
       'rt half children school due covid19 access computer globa
l education coalition',
       'rtcalorx public school ghatlodiaahmedabad established exc
ellent national reputation adopting globally benchmarked',
       'rt 50 students around school due covid19 access household
computer world',
       'rt using mobile phone great way stay connected ensure lea
rningneverstops covid19 crisis'],
```

Figure 3 Dataset based on keyword “Corona Disease” (5 tweets).

Table 1 Number of positive, negative and total tweets in dataset.

Dataset	Positive tweets	Negative tweets	Total tweets
Dataset 1	1,291	2,251	3,542
Dataset 2	11,041	3,030	14,071
Dataset 3	11,511	4,314	15,825

Analysis using machine learning

Machine learning algorithms are best for sentiment analysis as it is capable to identity the polarity of text without understanding the context in text. There are many learning algorithms that can be used for this purpose. As every machine learning (ML)/deep learning (DL) algorithm has its own merits and demerits in the proposed work different learning algorithms are taken in consideration and their results are compared. Sentiment analysis on tweets taken as a dataset is done using machine learning algorithms. The dataset is divided into 2 parts in the ratio of 8:2 for training and testing the model.

Among different machine learning algorithms, we have chosen Logistic Regression for our work. Logistic Regression is much easier to implement and used for binary classification (positive and negative tweets).

Using Logistic Regression, we will fit a "S" shaped curve giving probabilistic values lying between "0" and "1". Its equation is as follows:

$$\log\left[\frac{y}{1-y}\right] = a_0 + a_1x_1 + a_2x_2 + \cdots . a_nx_n$$

here y specifies the probability of the occurrence of an event, and a_i denotes the regression coefficients and x_i specifies explanatory variables [19]. Logistic Regression is applied on the dataset 2, and the results observed is shown in **Figure 4**. The test accuracy of the model received is 0.903.

```
LogisticRegression(C=1.0, class_weight=None, dual=False,
fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Figure 4 Output of logistic regression.

The research work is carried out in six stages using various machine learning algorithms base on their advantages and disadvantage. The selection of a machine learning algorithm in each stage is made to overcome the limitation of its previous stages, shown in the Figure 5 & 6. The first three stages use basic ML algorithms, and the last three stages are based on deep learning (DL) algorithms. The excremental results obtained in each stage are further discussed in this paper.

Machine Learning (ML) Algorithms

	Count Vectorizer and Logistic Regression	
Stage I	Purpose	To extract all unique frequent words and their frequency.
	Advantages	All frequent words are extracted.
	Limitations	Ignore rare words that might be important.

	TF-IDF vectorizer and Logistic Regression	
Stage II	Purpose	Works on word weightage based on the frequency of the word in the document. Find out temporal Words that are fascinating.
	Advantages	New temporal words found that can be used to detect hidden contents.
	Limitations	Works on unigrams/single words and provide limited information.

	n-gram and Logistic Regression	
Stage III	Purpose	Taken n =2 , bigrams are more fruitful
	Advantages	Temporal with seed words could give more information and improve text classification
	Limitations	Not accurate for complex problems with a huge data set

Figure 5 Research stages based on Machine Learning Algorithms.

Deep Learning (DL) Algorithms

Stage IV	**Deep Neural Network (DNN)**	
	Purpose	DNN is used for complex problems
	Advantages	Performs well for sentimental analysis
	Limitations	Time complexity is high.
Stage V	**Convolutional Neural Network (CNN)**	
	Purpose	Time complexity is comparatively low as compared to DNN
	Advantages	Low pre-processing required and in-depth results.
	Limitations	Good for short text. Difficult with long text.
Stage VI	**Recurrent Neural Network (RNN)**	
	Purpose	Use internal state memory for better analysis
	Advantages	Useful for time series and sequential data.
	Limitations	Time-consuming process

Figure 6 Research stages based on Deep Learning Algorithms.

The different machine learning algorithms used for this are:

Machine learning (ML) algorithms
1) Countvectorizer and logistic regression
2) TF-IDF vectorizer and logistic regression
3) n-gram and logistic regression

Deep learning (DL) algorithms
4) Deep neural network (DNN).
5) Convolutional neural network (CNN)
6) Recurrent neural network (RNN)

The 3 machine learning algorithms used for sentimental analysis using in the proposed work are Count Vectorizer & logistic regression, TF-IDF vectorizer & Logistic Regression and n-gram & Logistic Regression. The results obtained by the different machine learning models are discussed further in this paper.

CountVectorizer and logistic regression

CountVectorizer is used to make a vector of text data as a machine learning algorithm needs numerical data for its processing. In this method, a vocabulary of the word of the text is identified. The size of the vector is the numbers of words in the vocabulary. If a word is found in the text, then the data features, which is vocabulary word is set to 1. If the word is reencountered, then the count is increased. In simple words, CounterVectorizer finds all the different words in the text and the frequency of these words.

The logistic regression with CountVectorizer [13] is used on all 3 data set and the results were observed as follows. The feature extracted from Dataset 1 is 2,715 and the test accuracy of the model received is 0.965. The extracted features from Dataset 2 are 5,242 and the test accuracy of the model is 0.974. Further, Dataset 3 has 6,513 extracted features and the test accuracy of the model is 0.974. The smallest coefficients and the largest coefficients obtained for all dataset is shown in **Table 2**.

Table 2 Smallest coefficients and largest coefficients.

	Dataset 1	**Dataset 2**	**Dataset 3**
Smallest coefficients	'wrong' 'illegal' 'single' 'fake' 'due' 'behind' 'markaz' 'serious' 'bloody' 'unfortunate'	'killed' 'secret' 'behind' 'fake' 'evil' 'base' 'wrong' 'due' 'bad' 'mean'	'due' 'remote' 'difficult' 'mean' 'long' 'hard' 'forced' 'closed' 'devastating' 'tough'
Largest coefficients	'good' 'new' 'responsible' 'positive' 'first' 'supporting' 'many' 'secular' 'much' 'true'	'top' 'many' 'love' 'good' 'first' 'new' 'great' 'man' 'sure' 'kind'	'many' 'free' 'new' 'great' 'good' 'educational' 'top' 'latest' 'important' 'right'

The receiver operating characteristic (ROC) curve is shown in **Figure 7** for Dataset 1, **Figure 8** for Dataset 2, and **Figure 9** for Dataset 3. Words cloud for the top 50 words is also drawn that is shown in the **Figure 10**.

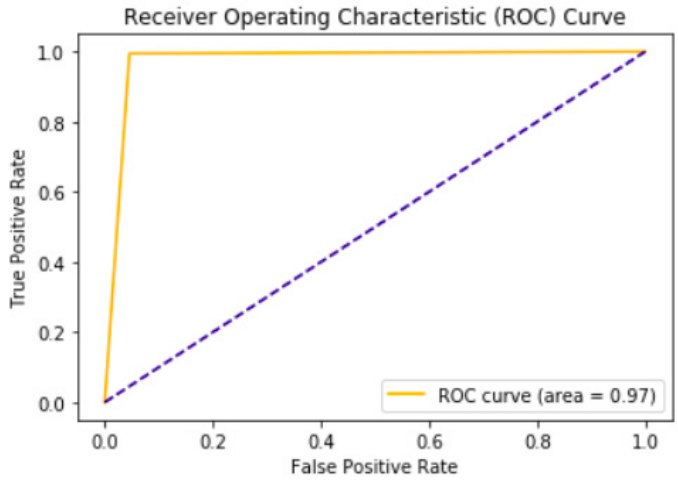

Figure 7 ROC curve for Dataset 1.

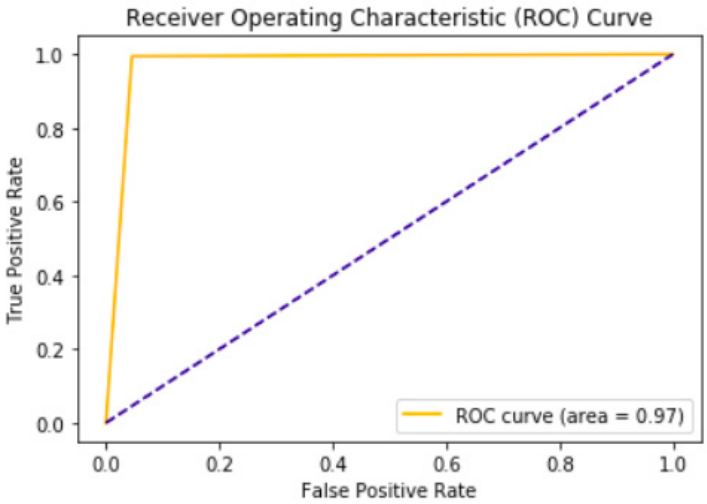

Figure 8 ROC curve for Dataset 2.

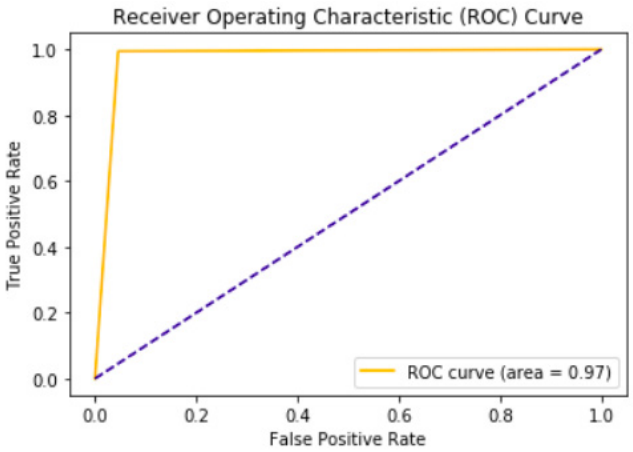

Figure 9 ROC curve for Dataset 3.

Word cloud for the top 50 words is also drawn that is shown in the **Figure 10**.

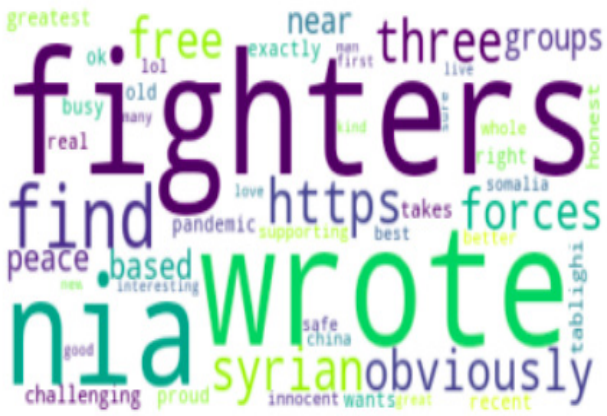

Figure 10 Word cloud for top 50 words using CounterVectorizer & logistic regression.

Table 3 Confusion matrix for Dataset 1, Dataset 2 and Dataset 3.

	Dataset 1		**Dataset 2**		**Dataset 3**	
	Positive	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
Positive	413	16	584	28	853	41
Negative	9	217	12	2,191	11	2,260

2) TF-IDF vectorizer and logistic regression

Like CountVectorizer, TF-IDF (term frequency-inverse document frequency) is also used to make a text vector. ConterVectorizer is based on the frequency of the word in the text. This approach may sometime lead to ignorance of rare words as its frequency would be less than others. Therefore, further in the proposed work, a TF-IDF & logistic regression model is implemented. TF-IDF works on considering word weightage in the overall document. The weights are measured based on how often word is seen in the text. TF-IDF are word recurrence scores that attempt to feature words that are all the more fascinating.

TF-IDF as compared to CounterVectorizer focus on more temporal terms that are more recurrent in a document but not across documents [14].

The logistic regression with TF-IDF [14] is used on all 3 data set and the results were observed as follows. The feature extracted from Dataset 1 is 602 and the test accuracy of the model received is 0.944. The extracted features from Dataset 2 are 1,417 and the test accuracy of the model is 0.95878. Further, Dataset 3 has 2,514 extracted features, and the test accuracy of the model is 0.941. The smallest coefficients and the largest coefficients obtained for all dataset is shown in **Table 4**.

Table 4 Smallest coefficients and largest coefficients.

	Dataset 1	**Dataset 2**	**Dataset 3**
Smallest coefficients	'wrong' 'markaz' 'illegal' 'fake' 'construction' 'nizamuddin' 'single' 'building' 'municipal' 'due'	'killed' 'chad' 'fake' 'secret' 'behind' 'base' 'evil' 'bad' 'wrong' 'due'	'due' 'remote' 'closed' 'difficult' 'mean' 'long' 'hard' 'school' 'forced' 'little'
Largest coefficients	'good' 'secular' 'new' 'positive' 'responsible' 'many' 'supporting' 'first' 'sure' 'much'	'top' 'many' 'love' 'first' 'good' 'new' 'muslim' 'man' 'great' 'takes'	'new' 'many' 'free' 'great' 'good' 'important' 'educational' 'first''right' 'latest'

Word cloud for the top 50 words is also drawn that is shown in the **Figure 11**.

Figure 11 Word cloud for top 50 words using TF-IDF & Logistic Regression.

Using TF-IDF some new temporal words have been extracted out like 'top', 'love', 'good', 'many' etc.

The receiver operating characteristic (ROC) curve is shown in **Figure 12**.

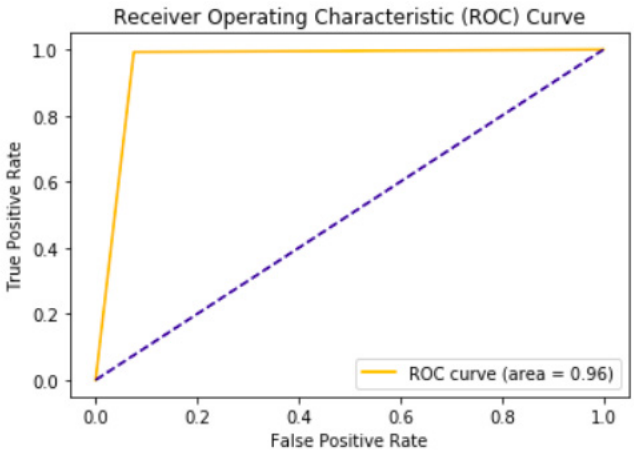

Figure 12 ROC Curve.

n-gram and logistic regression

n-grams is used in natural language processing (NLP) to improve matches in text. The value of 'n' in n-gram tells how many letters of words are matched. The higher value of 'n' helps reducing feature set. The 2 significant advantage of using n-gram are its scalability and simplicity. Further, to advance the representation of features for analysis is done using n > 1. The unigrams will provide only limited information, while bigrams can be more fruitful. Temporal words, along with seed words, could give more information and will improve the text classification [17].

The logistic regression with n-grams is further used on all 3 data set and the results were observed as follows. Document frequency of 5 and extracting 1-gram and 2- gram. The feature extracted from the Dataset 1 is 1,120 and the accuracy of the model received is 0.954. The extracted features from Dataset 2 are 3,038 and the test accuracy of the model is 0.985. Further, Dataset 3 has 6,712 extracted features, and the test accuracy of the model is 0.981. The smallest coefficients and the largest coefficients obtained for all dataset is shown in **Table 5**.

Table 5 Smallest coefficients and largest coefficients.

	Dataset 1	**Dataset 2**	**Dataset 3**
Smallest coefficients	'wrong' 'behind' 'serious' 'due' 'fake' 'bloody' 'unfortunate' 'single' 'illegal' 'foreign'	'evil' 'wrong' 'behind' 'killed' 'due' 'dangerous' 'bad' 'fake' 'hate' 'least'	'remote' 'difficult' 'hard' 'due' 'tough' 'mean' 'past' 'closed' 'long' 'behind'
Largest coefficients	'good' 'sure' 'new' 'positive' 'first' 'responsible' 'many' 'much' 'great' 'true'	'many' 'good' 'first' 'love' 'new' 'top' 'kind' 'sure' 'live' 'great'	'many' 'free' 'new' 'great' 'good' 'latest' 'live' 'top' 'better' 'first'

Deep learning (DL) algorithms are very efficient in solving complex problems with massive data. These algorithms are based on the way a human brain works. DL is also a machine learning but in an advanced form.

Further in the proposed work sentiment analysis DL are used to improve the classification of tweets. Three DL algorithms are implemented and tested for their accuracy. The algorithms are DL network, CNN, and RNN. The implementation of these algorithms needs to tokenize the tweets and padding them. For these models, the size of all the tweets should be the same so padding with a character is done at the

end of each shorter tweet to make all tweets equal in length. Words embedding is done to present tweets in a dense vector representation

To perform word embedding on data glove word embedding file of 100 dimensions has been used and weights for the embedding layer have been learned as shown in **Figure 13**.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 100, 100)          274100
_________________________________________________________________
flatten_1 (Flatten)          (None, 10000)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 10001
=================================================================
Total params: 284,101
Trainable params: 10,001
Non-trainable params: 274,100
_________________________________________________________________
None
```

Figure 13 Word embedding.

Deep learning network

An artificial neural network (ANN) with many hidden layers between input and output layer is known as deep neural network (DNN). It helps in dealing with complex problem with massive data. The structure is based on working of human brain. Sentimental analysis is a complex problem of text analysis which can be achieved using DNN [16].

Deep learning algorithms are used to train and test the model for all 3 datasets. Adam optimizer algorithm is used in python. The model is trained on a batch size of 128 with epochs 10 and 15. The training and validation split of data is done in the ratio of 8:2. The results obtained are shown in **Table 6**.

The analysis of results shows that Deep learning model test accuracy for the Dataset1 is around .90 whereas the test accuracy for other datasets has good accuracy of 0.948 and 0.98 for 15 epochs. The model accuracy and model loss for Dataset1 is shown in **Figures 12** and **13** respectively.

Table 6 Deep learning model accuracy.

	Dataset 1		**Dataset 2**		**Dataset 3**	
Epochs	10	15	10	15	10	15
Training accuracy	0.963	0.951	0.965	0.982	0.949	1
Validation accuracy	0.88	0.873	0.946	0.951	0.938	0.985
Test accuracy	0.915	0.905	0.945	0.948	0.94	0.98

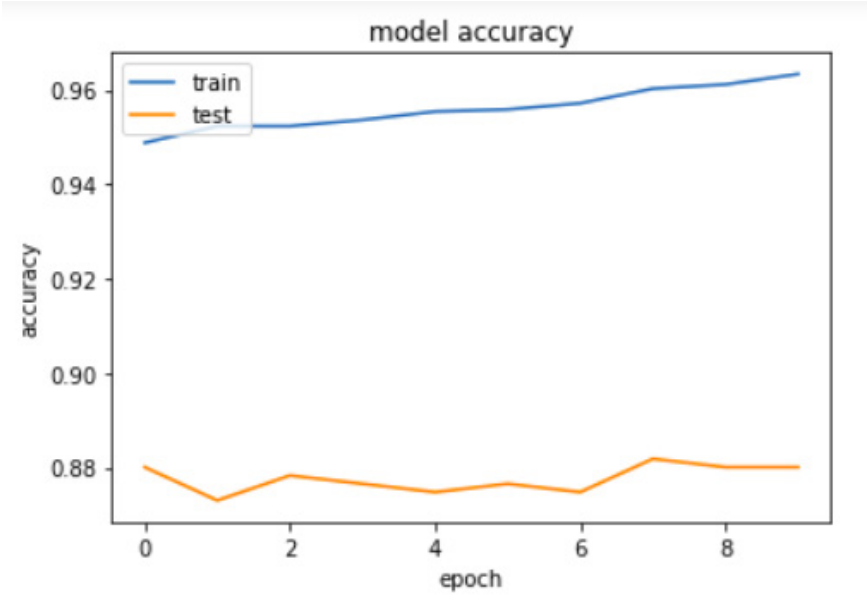

Figure 14 Model accuracy for Dataset 1.

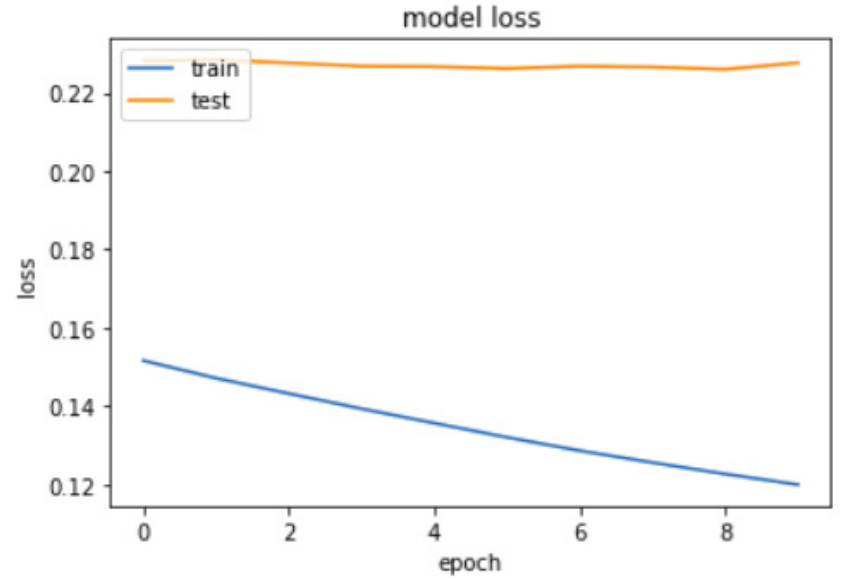

Figure 15 Model loss for Dataset 1.

CNN

CNN is generally used for image classifier. The sentiment analysis can also be done using the same algorithm by converting text as a vector of equal length and padding it. In the proposed work, this implemented model is also checked for its accuracy under the DL algorithm category [17].

The CNN model [15] is trained with a batch size of 128 for 6 epochs. Embedding layer followed by 1D convolution of 128 filters of size 5×5 (relu activation), followed by global max pooling and dense layer with 1 neuron. The model for all dataset is trained separately and the experimental results obtained is shown in **Table 7**.

Table 7 CNN model accuracy for Dataset 1, Dataset 2, and Dataset 3.

	Dataset 1	**Dataset 2**	**Dataset 3**
Epochs	6	6	6
Training Accuracy	0.987	0.999	0.996
Validation Accuracy	0.9171	0.972	0.982
Test Accuracy	0.933	0.975	0.933

Table 7 shows that the test accuracy for Dataset 1 is 0.933, Dataset 2 has a good test accuracy of 0.975 and Dataset 3 has an accuracy of 0.933. The model accuracy and model loss graph for the first data set is shown in **Figures 16** and **17**, respectively.

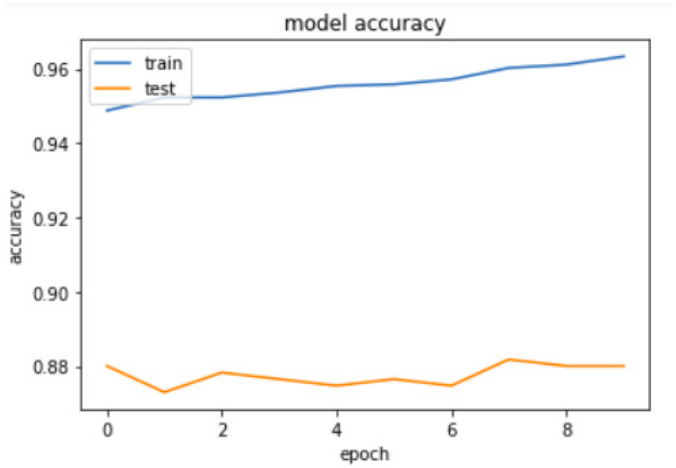

Figure 16 CNN model accuracy for Dataset 1.

The loss of a model shows prediction error by the implemented model. Gradients are calculated using a loss function and further, it helps in updating a weight in a neural network.

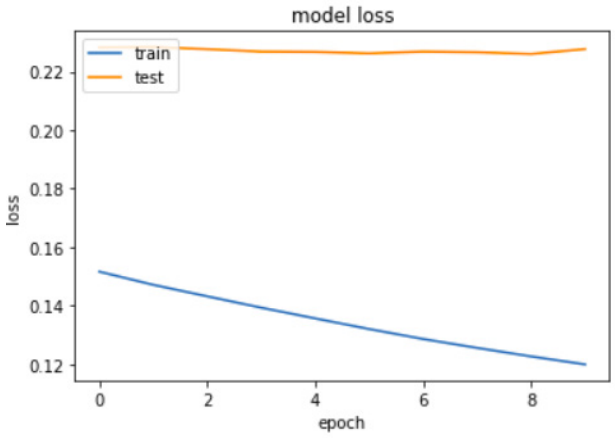

Figure 17 CNN model loss for Dataset 1.

RNN

In a traditional neural network, all the data input and outputs are independent of each other. RNN is a neural network where input and outputs are dependent. The output of the previous stage is fed as input to the current stage. RNN is good to use where the sequence has importance in the case of text for sentimental analysis [17].

In the RNN model for all dataset embedding layers followed by 128 LSTM layer is, 1 layer with 1 neuron and sigmoid activation is used. The model accuracy for all the datasets is shown in **Table 8**.

Table 8 RNN model accuracy for Dataset 1, Dataset 2 and Dataset 3.

	Dataset 1	**Dataset 2**	**Dataset 3**
Training accuracy	0.640	0.786	0.732
Validation accuracy	0.652	0.781	0.72
Test accuracy	0.605	0.782	0.717

The graph for model accuracy and model loss is shown in **Figures 18** and **19** for the first dataset.

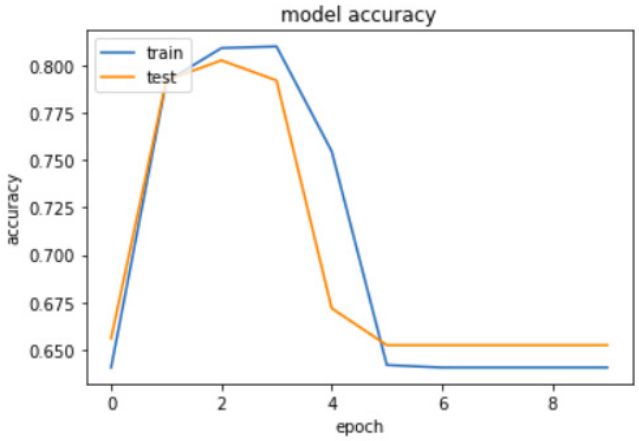

Figure 18 RNN model accuracy for Dataset 1.

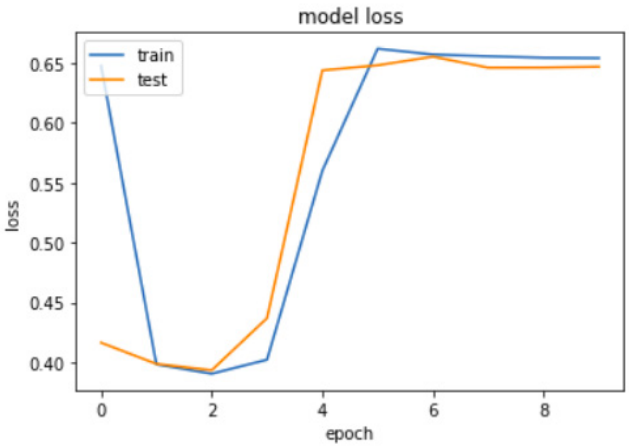

Figure 19 RNN model loss for Dataset 1.

Conclusions

The sentiment analysis of the tweets based on the radical activity keywords using different machine learning algorithms is summarized in **Table 9**.

Table 9 Summary of all model accuracy.

Machine learning algorithms	Accuracy of the model		
	Dataset 1	**Dataset 2**	**Dataset 3**
CountVectorizer and logistic regression	0.965	0.974	0.974
TF-IDF vectorizer and logistic regression	0.944	0.958	0.941
n-gram and logistic regression	0.954	0.985	0.981
Deep learning network	0.915	0.948	0.98
CNN	0.933	0.975	0.933
RNN	0.605	0.782	0.717

The analysis of the results shows that a machine learning algorithm may be helpful in identifying a radical activity over a social platform like Twitter. CountVectorizer using logistic regression has a model accuracy of more than 95 %. Whereas in the case of the deep learning machine model the CNN has the best accuracy i.e., above 93 %. The simulation results also show some new words with the seed hashtag like 'top' 'many' 'love' 'good' 'first' 'new' 'great' 'man' 'sure' 'kind' having the highest polarity.

Further, the number of tweets in the dataset can be increased to get better model accuracy and the dataset with different keywords based on radical activity can be combined to train and test the model to get better results.

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