GRADIVA

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Effective Deep Learning Approach for Genuineness of Twitter's Views Using Sentiment Analysis

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Abstract

Social Media has tremendously achieved digital advancements in the field of Information technology. The users have tools such as Twitter, micro blogging sites and blogs for sharing everyday life events, views regarding products and services, and news. Individual shares opinions, views and thoughts posts in digital form using social media sites. The most advanced and widely used social media site is Twitter, through people share their views, reviews, and opinions and broadcast them. Due to this activity, ample views and comments are being share by users on various social media platforms, e-commerce platforms, websites, and blogs. The user posts the opinion or view as positive or negative of any product sometimes leading to appraise the product or damage a product or business reputations. These views shared by the user on various platforms are not genuine or true. It may be fabricated, false, or spam. In this paper we proposed BiLSTM deep learning techniques with incorporating and combined twitter users' features to predict the genuineness of views. The results obtained in experimentation were optimum over the traditional state of art methods. The newly build hybrid approach presented the best performance considering accuracy, F1 score, Precision and Recall .The results of the conducted experiments demonstrates ample accuracy , precision and recall.

Index Terms: *Social Media, Twitter, Genuineness of Views, Data Collection, Deep Learning, Machine Learning.*

I. INTRODUCTION

Sentiment Analysis is a computational approach to studying people's attitudes, emotions, and opinions toward an entity. The entity can be individual, events, or topics. Sentiment analysis extracts the sentiment from the given text and analyzes and classifies the polarity. Online social media plays a vital role in human life, and is an essential medium to communicate and share views, opinions, and many other things on social media [1].Social media is one of the emergent standards used for communication through which millions of internet users share, criticize and review any product, people, services, etc.

The availability of platforms enables people sitting far apart to understand things, matters, and situations around the globe. Social Media incorporates a variety of socially connected platforms sites like Facebook, Twitter, Instagram, and many micro blogging sites where users share their views. Social Media encompasses many topics like advertising on social media, election campaign drives, social media analysis, microfinance and economics [2].In recent past few years, the use of social media for sharing views has increased rapidly. Users share their views regarding product purchases and various services used by the users.

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In the 21st century, Due to the availability of communication devices like smartphones, laptops, and palmtops, permitting to interact individually result in the generation of big data. Social Media such as Twitter has millions of users sharing more than 175 million tweets per day require a great space to store the data.

Sentiment Analysis is one of the emerging, promising, powerful techniques applied in various areas such as Recommendation building, Customer Relationship Management, spam detection, anomaly, spammer discovery etc. [3]. The user's shared views regarding any product, people, or services on social media are not always legitimate and genuine. They often share spam, illegitimate, untrue views.

The aim is to design and implement an effective approach for the genuineness of view. To deal with problem of genuineness of views, requires designing a framework. The different researchers worked on spam detection in messages, detection of spam on Twitter, and detection of spam users or not. The researchers used distinct domain datasets are readily available on websites and depositories such as UCI and Kaggle.

The techniques use by the researchers was simple, and dataset was also not the primary one. The data required for this research was collected from Twitter using various hash tags. The various data transformation techniques, tools, and techniques being use. Today words every user used some medium for communication. This communication can be performing using certain media, platforms and micro blogging sites.

Mostly the users used social media platforms such as the Twitter, E-Commerce sites such as Amazon, Flipkart, and different micro blogging sites for sharing their views. Due to impact of this, many social media sites, E-commerce sites flooded with ample views. These views shared by the users are not always genuine, or truthful. It's often spam, fabricated, and false [4].

To handling the problem of genuineness and influence measurement, the research aim is to design and develop an Effective approach for the genuineness of Views shared by the user. Most researchers address the spam detection problem using a single approach or technique. Due to this, the accuracy and performance are not up to the mark. The approach Effectiveness is due to the presence of the hybrid approach. The approach consists of various techniques and methods which work together.

II. CONTRIBUTION OF WORK

In this research article, the main objective is to design and implement the hybrid approach for identification of the genuine views from various collected views and measures the influence of views shared by the user. For hybrid approach we combined the Sentient Polarity of views along with the various tweet features.

The contribution of this paper in identification of genuineness of views and to measure the influence of the views is as follows.

1. Most of the existing research work used already available dataset for testing and training and performed the experimentation. In this approach, we have designed a separate framework for data collection using API called as TwitterAPIV2.More than 400000 views from different domains are collected along with its objects and features.

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2. Pre trained model used for word vector representation to gain the nearest contextual, semantically related meaningful expression of text present in the dictionary. The Glove (Global Vectors for Word Representation) Pre trained model is used for word vector representation.
3. In the existing works, simple tweet features were considered while analyzing the sentiment. In the proposed approach, a various features are considered for sentiment analysis and for genuineness of views.
4. Built a hybrid model for detection of genuineness of views combining Sentiment Polarity and the various tweet features.
5. The performance of the hybrid approach outperformed the state of art machine learning and single Deep learning model. The proposed deep learning model namely Hybrid BiLSTM achieved better accuracy.

The workflow of the research article is dividing into various sections. Section 2 is related to Literature Review related to spam detection, datasets used for spam, and techniques. The Section 3 focuses on the data collection, preprocessing, and the proposed framework. Section 4 represents the Result and comparative analysis of work with state of art. Section 5 consists of conclusion of the work performed.

III. RELATED WORKS

In recent years, sentiment analysis has become a well-established research area, offering organizations and business tools for tracking and analyzing consumer attitudes toward their goods, brands, and services. Plenty of research was conducted in this direction, primarily focusing on the sentiment analysis of the conventional text involved in discussion forums, blogs, and review data. However, the rapid growth of social networks and micro blogging services has significantly changed.

The focus of the research shifted to the sentiment analysis of micro blogging data, spam text detection, user accounts, and specific tweet data. A one of the most widely used micro blogging platforms; Twitter generates content that reflects opinions on subjects, products, life events, and people. Many different approaches have been use in existing work on sentiment analysis. These approaches were the traditional approach, Machine learning approach, Hybrid approach, neural networks, and Deep learning approach.

Mohawesh R. et al. [9] have presented, reviewed, and analyzed the different techniques, summarizing the currently available datasets and methodology for collection. They have classified the detailed survey into two groups: traditional ML-based and Deep Learning based.

They have conducted the study of Standard of excellence techniques of neural network models is not yet explored. Each method is explore for Fake reviews detection and is explained independently. Feature extraction methods are reviewed in detail with advantages and disadvantages. They have also pointed out the various challenges identified by authors while reviewing the various research articles.

Machine Learning-Based Classification

Chen C.et al. [5] effortly design robust detection techniques using many attitudes such as user data, analysis of features, and prominently used models. Twitter provides a ready API to continue data extraction and collection to construct the dataset.

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The author has considered 12 varied features for extraction classified into User-based and Twitter-based properties directly parsed from a JSON structure. More experiment was performed to show the changes that occur during the testing done on a particular day to observe the changes in detection rates of spam and non-spam.

Adewole, K. S. et al. [6] developed a single solution for spam message detection and account detection. To perform experimentation, the author recycled datasets domains related to spam messages from SMS and Twitter micro blogs. The author used an evolutionary search algorithm with 18 features collected from the database for analysis. To increase the effectiveness of spam detection, the author has used clustering techniques such as PCA and tuned k means clustering. Due to clustering, they found nasty message communication. They combined the clustering and the classification approach to increase the classification accuracy of the classifier.

Lexicon Based Classification

Arif, M.et al. [7] presented a new encoding method to characterize the classifier rule. The proposed model consists of the different phases used for the classification of tests. The author proposed a new classifier which is the next version of XCSR. The designed method can handle simple features using feature engineering. There is an improvement in the XCSR# method with the help of sentiment-specific features.

Hybrid Methods Based Classification

Alom, Z. et al. [8] proposed and implemented two different classifiers, such as based on simple Text and the Text addition with the Users Metadata called a combined Classifier. The authors used Convolution Neural Network in both the classifiers and exploited CNN as it is capable of finding the difficult and complex patterns from the text and its less computational time.

Neural Network Based Classification

Barushka A. et al. [9] presented a novel spam filter integrating feature extraction from distribution-based algorithms with a deep neural network model. This model helps to find the complex structure, and no dimensionality reduction is required.

Guo Z. et al. [10] proposed and implemented a deep graph neural network framework to detect spam in the network. This framework is form to extract the features of a social graph. Due to this type, this framework can acquire the most valuable information to gain the accuracy of the spammer. The Social media consist of heterogeneous network where users are connected in cyberspace. The author has proposed a deep neural network framework for mining the proper relation between the users in graph-based cyberspace and finding the unknown linkages between users.

Deep Learning Based Techniques

Jain G.et al. [11] worked and presented using the most impressive techniques like deep learning. For spam classification purposes the author's new deep architecture like Long Short Term Memory, this stands for Recursive neural networks. The advantage of using this architecture is to ideally learn whatever the hidden features are unable to detect by the traditional classifiers. They have used three features representation for vectors such as Word Net, ConceptNet, and WordToVec. The SLSTM architecture can study and learn automatically.

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Madisetty S.et al. [12] proposed an ensemble approach to detect spam in Tweets. They have used a combination of two different models, i.e. deep learning and Feature based provides the facility which acts as a Meta classifier. The Different word embedding techniques have been used (such as Word2Vec and Glove) for training a model. The author has used a combination of various models CNN and Twitter, CNN and Google News dataset, CNN and Edinburg database, CNN and Hspam dataset, and CNN and Random forest for comparison. The proposed model's performance is check with the other baseline model and the better combination of different models.

Wei F. et al. [13] worked and presented an RNN model to differentiate the Twitter Bot account from a human account. They have used the BiLSTM network with word embeddings. The proposed approach is the first ever approach consist of bidirectional LSTM (BiLSTM) with word embeddings. The author concluded that an RNN model, specifically BiLSTM, with word embeddings to distinguish Twitter bots from human accounts. The model requires no prior knowledge or assumption about users' profiles, friendship networks, or historical behavior on the target account.

Ensemble Based Classification

Vantaa. T.et al. [14] proposed and worked on combining different features collected from other researchers and features newly added features. The text blob tool is used to perform Natural language processing tasks. The method suggested by the authors parted into two vital parts: selection of features and methodology. The authors have designed and implemented a majority voting approach using various algorithms such as Convolution Neural Network and Long Short Term Memory, Support Vector Machine, and Multilayer Perceptrons Layer model. After applying Majority Voting, they obtained a prediction result of one considered as the output of the Ensemble Voting Classifier.

IV. MATERIAL AND MODELS

This section describes the Tweets dataset and features that has been used to develop the hybrid deep learning BiLSTM model. This section also describe the models develop for genuineness of views and influence measurement of the views shared by the user.

Dataset

The data collection and transformation is implemented using various tools and techniques. For collection of data, tweets are extracted from twitter with the help of the TwitterAPI called TwitterAPIV2. This TwitterAPI provides the end to end programming interface to interact with the TwitterAPI. In this research, the interface is designed and the interface can extract the number of tweets (views) from Twitter handles using Tweepy, a python library used to interact with the Twitter API.

The interface provides the “hashtag Based” Searching along with the number of Tweets to be extracted. The TwitterAPIV2 (version2) provides the various objects and its related fields to extract the information from the Twitter.

The various objects like Tweet, User, Space, List, Media, Poll and Place. Each object is related to its fields and TwitterAPI permits to extract the Public matrices only. The collection of various information related to the tweets are useful to extract the polarity and the influence measurement

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Table 1: Collected data from Twitter with various features

1	text_c	Protected	Verified	Retweet	ReplyCoun	LikeCount	QuoteCoun	lowersCo	istedCoun	iendsCou
2	visible gujarat people gujarat decid	0	0	0	1	1	0	275	0	1050
3	twocmodelofgujarat	0	0	0	0	0	0	298	13	137
4	etter dan dat dey decided give bjp	0	0	15	0	13	0	1670	8	2192
5	:y behind residence gujarat model	0	0	19	2	21	0	1670	8	2192
6	bjp pocso convict dankeseb abudha	0	0	0	0	0	0	10	0	86
7	urring examination paper leak hop	0	0	1	0	1		8	0	7
8	gedy one worst due govt negligenc	0	0	0	0	3	0	78331	127	26391
9	gedy one worst due govt negligenc	0	0	2	0	2	0	78331	127	26391
10	bjp limit give whole india still gree	0	0	0	0	0	0	1680	2	1255
11	andidate rajendra bhai patel congre	0	0	0	0	1	0	460	1	793
12	exposed reality gujarat model twoc	0	0	0	0	0	1	237	8	567
13	r candidate rajendra bhai patel con	0	0	39	0	36	0	2813	3	3016
14	lelofgujarat hardik patel bjp see ha	0	1	381	25	1635	4	522209	522	1895
15	year lot time given bjp gujrat time	0	0	0	0	1	0	460	1	793
16	ujarat dont fooled time gujrat gujra	0	0	0	0	1	0	460	1	793
17	li adi shankar acharya present time	0	0	0	0	1	0	460	1	793
18	ed life support government hospita	0	0	40	2	43	0	1533	0	1651
19	nent amp suicide add port gujarat b	0	0	108	4	107	0	1820	9	931
20	46356 fifaworldcup 1163877 twocm	0	0	71	1	77	1	9744	25	2459
21	046356 fifaworldcup 1163877 twocr	0	0	0	0	0	0	113	0	97
22	ibe plight unemployed youth twoc	0	0	1	1	1	0	113	0	97
23	sorry honesty try play modi want g	0	0	33	2	42	0	20854	12	20556

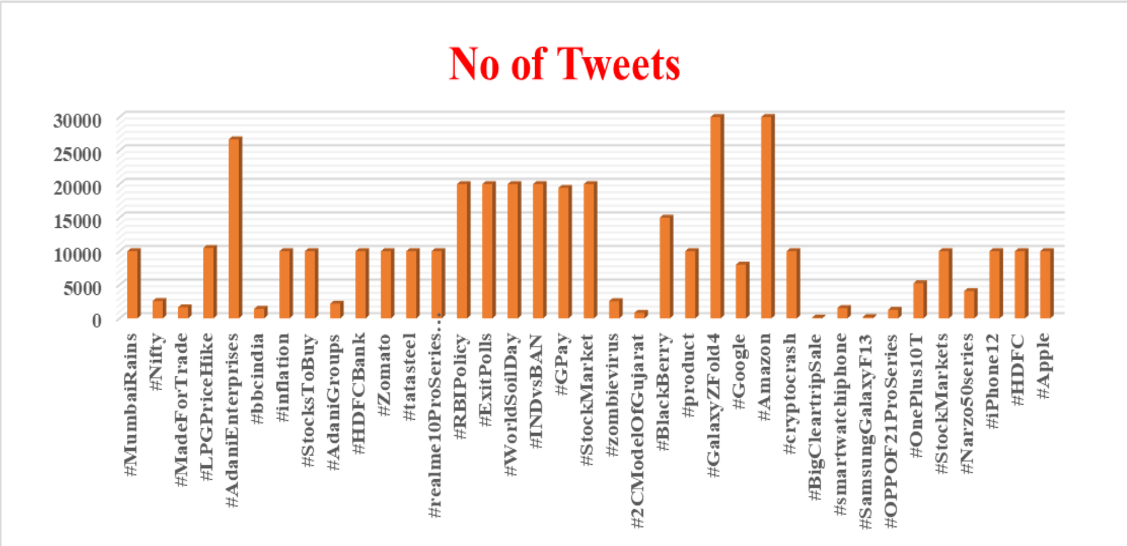

Figure 1: Hashtag and Number of Tweets collected from Twitter

Data Pre-processing

The extracted tweets from Twitter were in the raw data format. This raw unstructured data needs to be converted into structure form used for further processing. The data cleaning process is applied for data transformation. To ensure efficiency, smoothness, and effectiveness of the next processes the data is transformed from unstructured to structured form. The natural language processing steps were applied to clean and make machine-understandable data. The tool Natural Language Toolkit (NLTK) and spacy is used for the data transformation and applying natural language processing to datasets.

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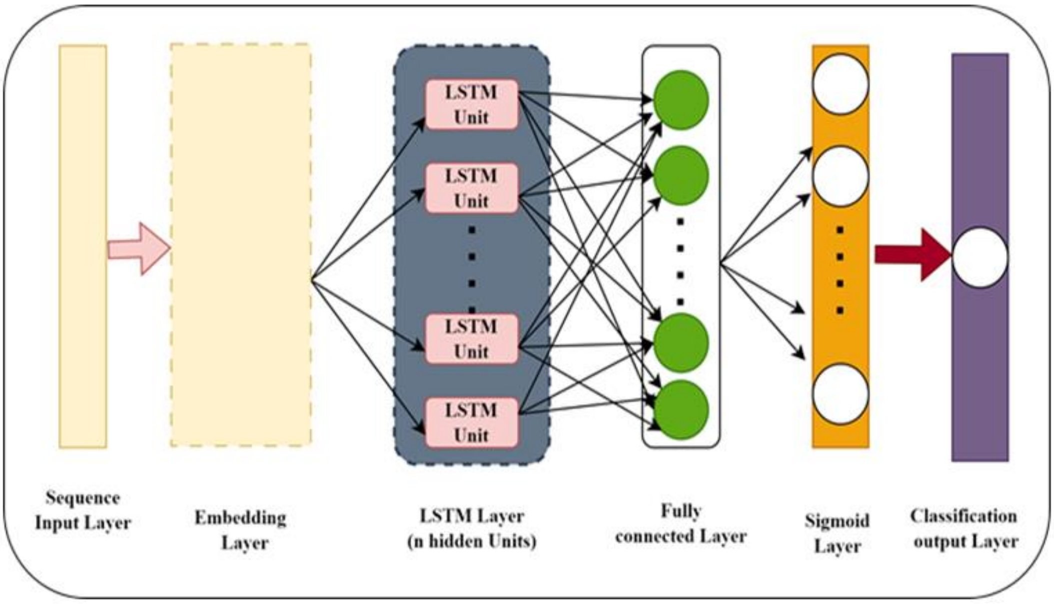

Figure 2: BiLSTM Architecture

Model of BiLSTM for Sentiment Polarity

The complete BiLSTM architecture for the Polarity detection using sentiment analysis as shown below. The architecture consists of 5 layers such as sequence input layer, LSTM Layer, fully connected layer, sigmoid layer and classification output layer.

Sequence Input Layer

The input to the BiLSTM model is sequence input text such as the sentences. This layer considers the series data as an input for the network. The input layer carries data samples as a sequence of unique indices of same length.

Models

This works builds on the BiLSTM model which is one of the deep learning architecture used for classification, prediction and regression problems. This works uses two BiLSTM model architecture of deep learning. The first BiLSTM model is utilized for determination of polarity of the tweets which are collected. The second BiLSTM model which is Hybrid model utilized for classification purpose. The aim behind the embedding matrix is to show every row depicts a unique index value. This unique value corresponds to the single unique word present in the vocabulary. The embedding matrix has a dimension of u * v, where u depicts the size of dataset vocabulary and portrays the dimension of a dense vector. In this research, a 300 dimensional word vector is used as a pre- trained word embedding vector.

Embedding Layer

This is the second layer of the BiLSTM system architecture called as Embedding layer. In this layer all the sequence input of same length is converted into real valued feature vector contains the value in numeric form. This real valued feature vector form layer is stacked on each other form a matrix called Embedding Matrix.

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LSTM Layer

Each LSTM network propagates the information in one direction i.e. forward direction only. This shows the information state of time t fully depends on the information available before t. However due to the propagation of the information in one direction, the whole semantic cannot properly characterize. To be more effective, the subsequent and the previous information is equally important and effective for semantic of the input reviews. A Bidirectional Model is employed which consists of two LSTM layers competent to read the input tweets from both i.e. forward as well as backward direction. The process which is forward starts scans and reads the input tweets from left to right and its hidden state can be shows as

$$htl = LSTM\ (xt, htl\text{-}1) \qquad \ldots\ldots..(I)$$

Whereas the backward starts from right to left and its hidden state can be shows

$$htr = LSTM\ (xt, htr\text{-}1) \qquad \ldots\ldots\ldots(II)$$

Finally BiLSTM output can be summarized by combining forward and backward hidden states such as Eq (I) and Eq(II) $ht = [htl, htr]$

Fully Connected Layer

A fully connected layer performs the series of nonlinear transformations on the values of the feature obtained by LSTM Networks vectors. The primary aim of this layer is to fully extract and prepare the features for the final stage. This fully connected layer is composed of many Hidden layers. In a Bidirectional Long Short-Term Memory (BiLSTM) network, the fully connected layer is added after the LSTM layer(s) in order to perform the final classification. The fully connected layer consists of a set of neurons that are connected to every output of the LSTM layer(s). The fully connected layer in a neural network serves as a powerful tool for transforming the output of the previous layer into a format that can be used for the final task.

Sigmoid Layer

In a Bidirectional Long Short-Term Memory (BiLSTM) neural network, the sigmoid function is used as an activation function in the gate mechanisms of the LSTM cells. The LSTM cell has three gates: the input gate, the forget gate, and the output gate. Each gate takes input from the previous hidden state and the current input, and then produces an output between 0 and 1 that controls the flow of information through the cell. The sigmoid function is used in the gate mechanisms because it can output values between 0 and 1, which is useful for controlling the flow of information. The sigmoid function is used to transform the input into a value between 0 and 1, which is then used to decide how much of the input should be let through the gate.

Classification Layer

The classification layer in a Bidirectional Long Short-Term Memory (BiLSTM) network is typically the last layer of the network, and is responsible for producing the final classification output. The classification layer is a specific type of fully connected layer that is designed to transform the output of the previous layers into a set of probability values that represent the likelihood of each class. The output of the classification layer is produced using a softmax activation function, which ensures that the probability values sum to 1 and can be interpreted as the probability distribution over the possible classes.

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Evaluation of Trained / Validation Losses for Trained Model

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 100, 100)          2000000

 bidirectional (Bidirectiona  (None, 100, 128)         84480
 l)

 bidirectional_1 (Bidirectio  (None, 64)               41216
 nal)

 dense (Dense)               (None, 1)                 65

=================================================================
Total params: 2,125,761
Trainable params: 125,761
Non-trainable params: 2,000,000
_________________________________________________________________
None
```

Figure 3: Different Layers of Model

Model of BiLSTM for Genuineness of views

The Genuineness of views model is designed using hybrid approach. The hybrid approach is unique and consists of the combination of the various tweets features collected from the twitter along with the tweets and the tweets Polarity obtained from the tweets. The hybrid model able to detect the genuineness of views shared by the user on the twitter. The dataset having the tweets with positive and negative polarity which is helpful to find the Genuineness of views combined with the Tweets features.

Table 2: Hyperparameters used in model

Sr. No	Name of Hyper Parameter	Actually Used	Value Assigned to Hyper Parameter
1	Input dimension	Input_dim	**100**
2	Activation Function	Activation	Relu
3	Vocabulary Size	Vocab_size	**20000**
4	Loss function	loss	binary_crossentropy
5	Training Split	Train_split	70%
6	Testing Split Size	Test_split Test	30%
7	Validations Split Size	Validation_split	10%
8	Batch Size	Batch_size	100
9	Learning Rate	lr	0.01
10	No of Epoch	Epoch	10

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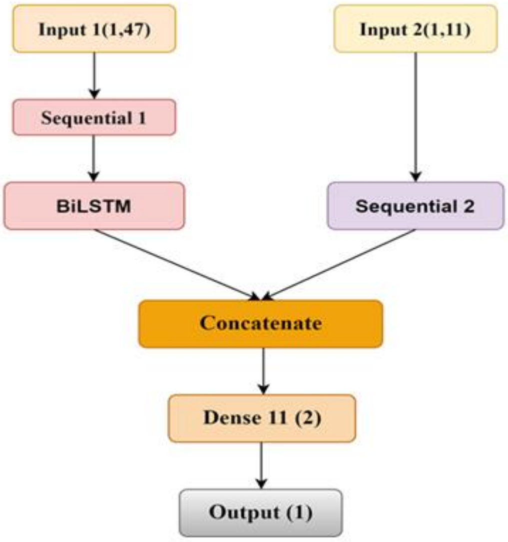

Figure 4: Hybrid Model for Genuineness of Views

This works uses two BiLSTM model architecture of deep learning. BiLSTM model which is Hybrid model utilized for classification purpose. The implementation of the model is done with the help of the keras which is deep learning API. This API provides the Functional Layer which is able to concatenate the two different input layers and generate the output. So Functional layer of keras takes the Multiple Input and Generate the Single Output. The Input1 is the model is the text and polarity with the maximum length of text is 47 words. The other Input is Input2 consisting of the various features of the tweets collected from twitter using Twitter API. To convert the text and polarity embedding is performed and Bidirectional Long Short Term Memory (BiLSTM) is used. The output of the BiLSTM is concatenate with the tweet features to generate the final output. The activation function such as Rectified Linear Unit (ReLU) and Sigmoid are used to generate the output. The Hybrid model classifies the tweets with greater accuracy.

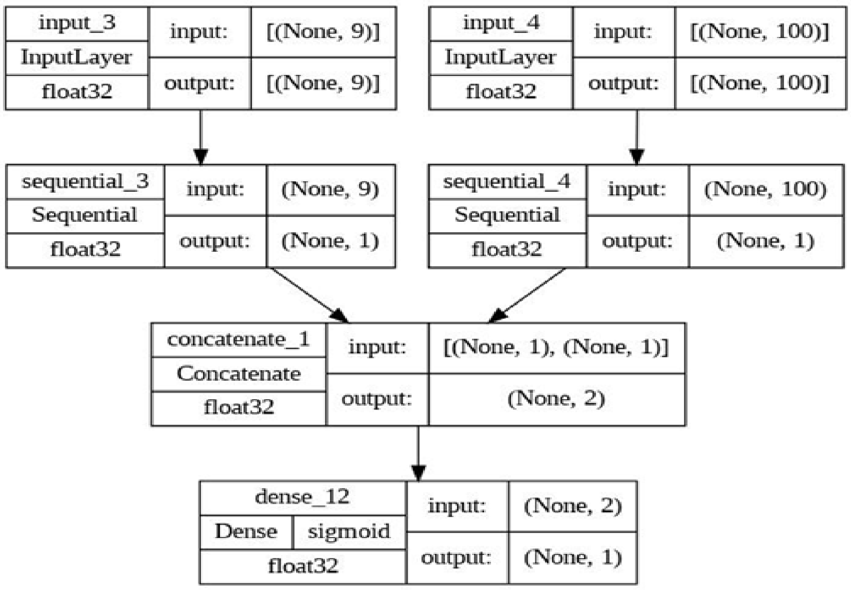

Figure 5: Model structure for Genuineness of views

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V. EXPERIMENTAL SETUP AND EVALUATION

For implementation, various tools and techniques were used. These tools and techniques were implemented on the datasets. The tool Natural language Toolkit (NLTK) and spacy is used for the data transformation and applying natural language processing to datasets. The data which is collected from twitter is not in supervised form. To perform experimentation , the supervised dataset is required. The collected data is converted into supervised form with the help of the Valence Aware Dictionary for sentiment Reasoning (VADER) which is Python based library for sentiment analysis. The Word2Vec tool is used to convert the views into the vectorized form to represent the Embedding matrix. The deep learning model such as BiLSTM is implemented for classification of tweets into various polarities. The keras deep learning API is used for the implementation of the Functional layer which combines the two different model into one model. The Functional layer of keras was used to combine and concatenate the two different models and generate the output.

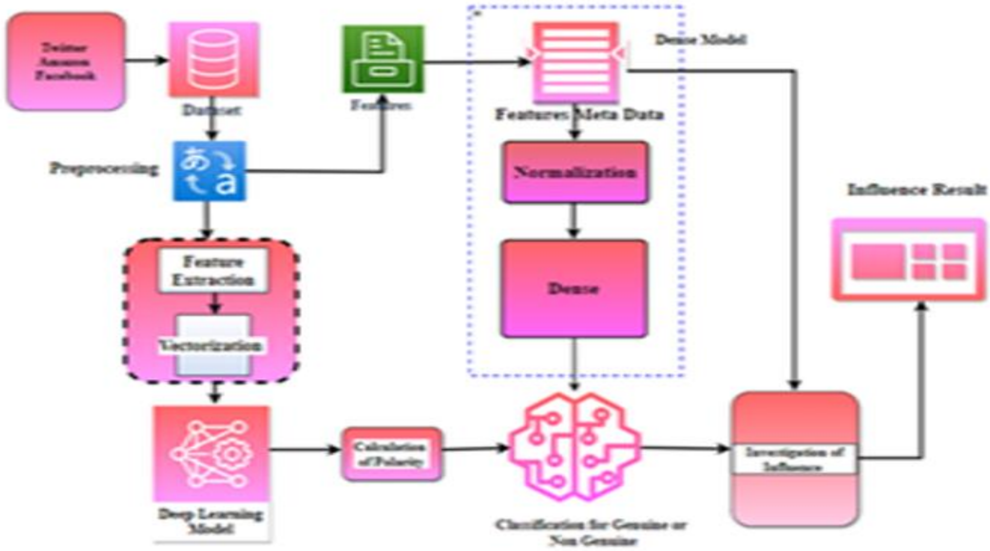

Figure 6: Framework for Genuineness of Views

Architecture of BiLSTM for Sentiment Polarity

The complete BiLSTM architecture for the Polarity detection using sentiment analysis as shown in Figure No.4. Architecture consists of 5 layers such as sequence input layer, LSTM Layer, Fully connected layer, sigmoid layer and classification output layer. The final layer called classification layer in a Bidirectional Long Short-Term Memory (BiLSTM) network is typically the last layer of the network, and is responsible for producing the final classification output. The classification layer is a specific type of fully connected layer that is designed to transform the output of the previous layers into a set of probability values that represent the likelihood of each class. The output of the classification layer is produced using a softmax activation function, which ensures that the probability values sum to 1 and can be interpreted as the probability distribution over the possible classes. The final layer called classification layer in a Bidirectional Long Short-Term Memory (BiLSTM) network is typically the last layer of the network, and is responsible for producing the final classification output. The classification layer is a specific type of fully connected layer that is designed to transform the output of the previous.

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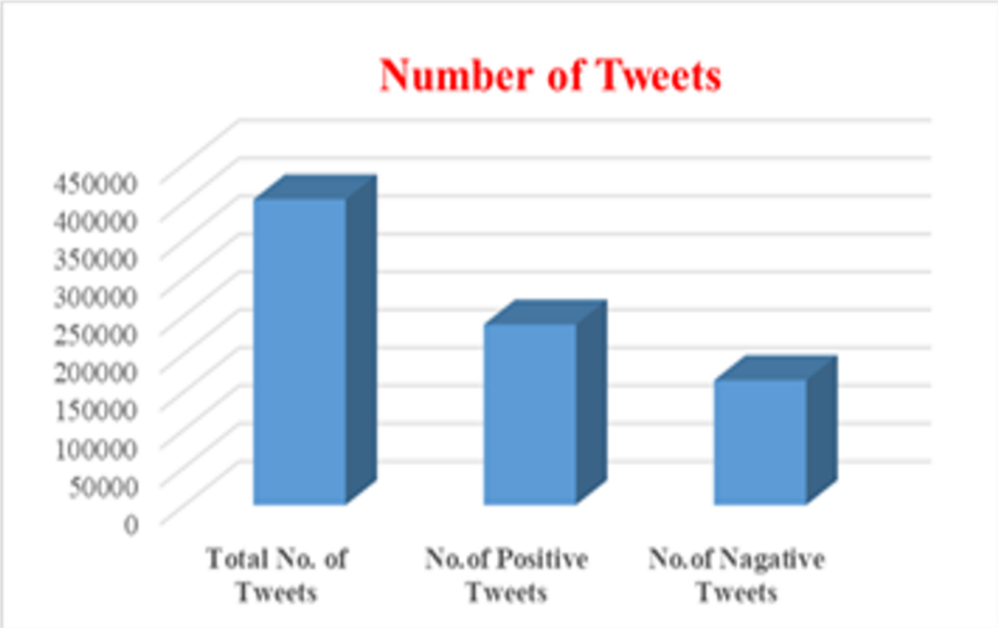

Figure 7: BiLSTM Architecture

Table 3: Positive and Negative Tweets

Sr. No	Total No. of Tweets	No. of Positive Tweets	Percentage of Positive Tweets	No. of Negative Tweets	Percentage of Negative Tweets
1.	403182	238322	59.1%	164860	40.9%

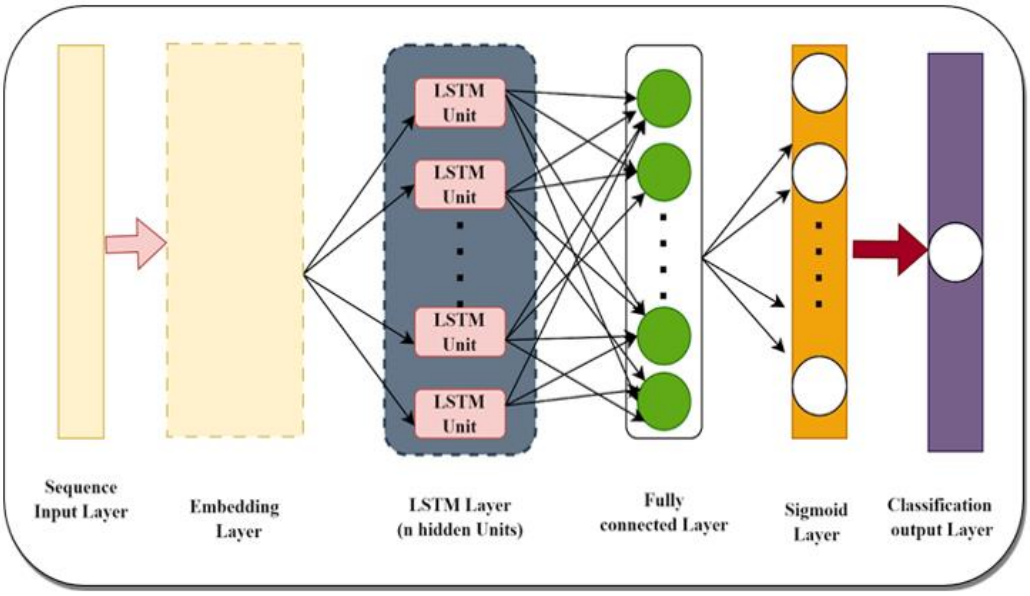

Figure 8: Polarity of Tweets (In Numbers)

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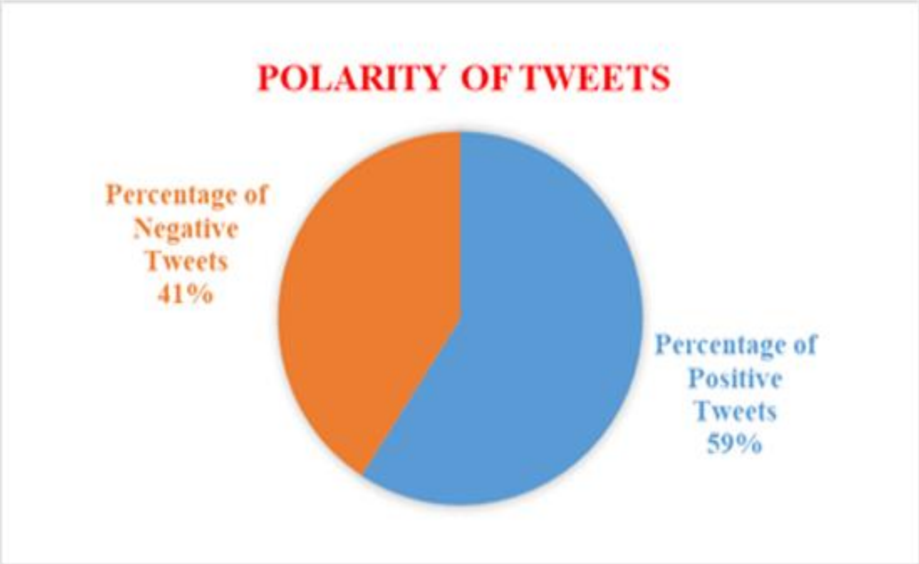

Figure 9: Polarity of Tweets (In percentage)

Figure 10: Word Cloud Showing Positive Polarity word

Figure 11: Word Cloud Showing Negative Polarity word

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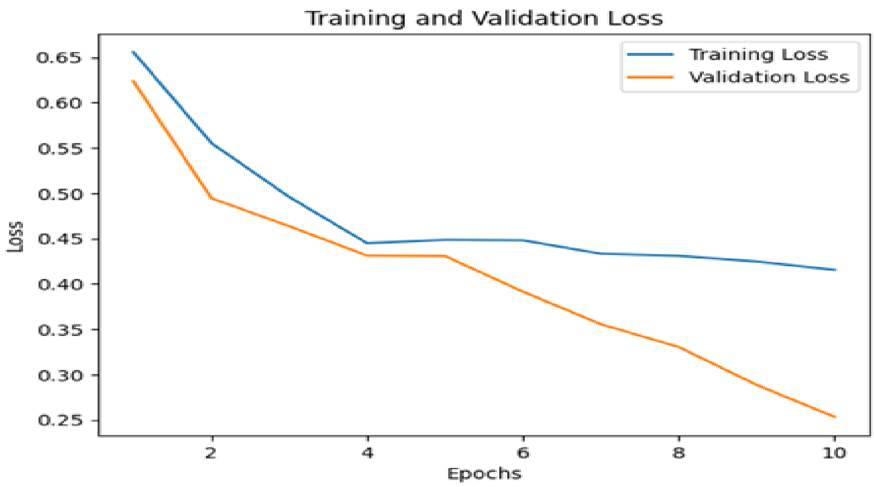

Figure 12: Training Loss versus Validation Loss (For Sentiment Polarity)

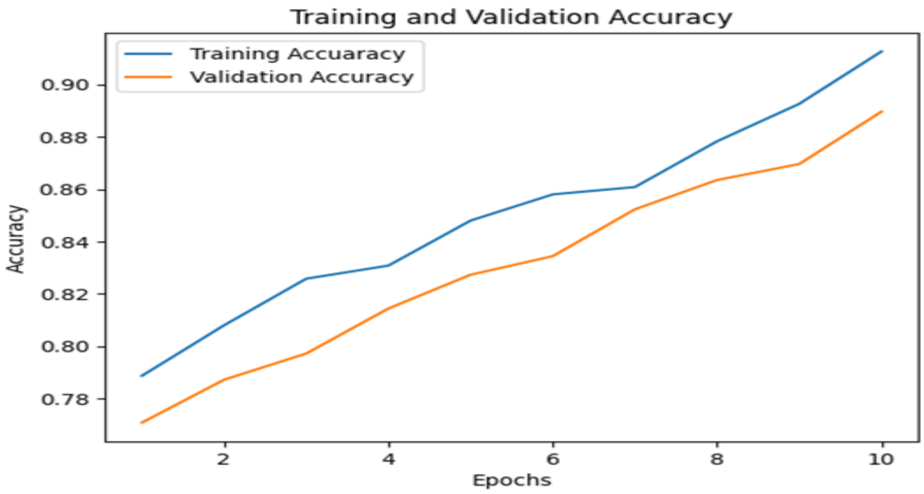

Figure 13: Training Accuracy versus Validation Accuracy (For Sentiment Polarity)

The Figure No.14 indicates the BiLSTM model Training and Validation loss for Sentiment Polarity. The model classifies the tweets up to the certain epochs. But models show over fitting after the certain number of epochs. Here in the Figure No 14. Indicates that up to the certain epochs the model having less loss but as soon as the model over fits the loss increases and trend has been changes from ascending or descending. The validation and training curve shows the bias and tradeoff of the model.

Classification Model Structure for Genuineness of views

The Genuineness of view model is designed using hybrid approach. The hybrid approach is unique and consists of the combination of the various tweet features collected from the twitter along with the tweets and the tweets Polarity obtained from the tweets. The hybrid model able to detect the genuineness of views shared by the user on the twitter. The dataset having the tweets with positive and negative polarity which is helpful to find the Genuineness of views combined with the Tweets features. The implementation of the model is done with the help of the keras, which is deep learning API. This API pro-videos the Functional Layer which is able to concatenate the two different input layers and generate the output. So Functional layer of keras takes the Multiple Input and Generate the Single Output. The Input1 is the model is the

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text and polarity with the maximum length of text is 47 words. The other Input is Input2 consisting of the various features of the tweets collected from twitter using Twitter API. To convert the text and polarity embedding is performed and Bidirectional Long Short Term Memory (BiLSTM) is used. The output of the BiLSTM is concatenate with the tweet features generates the final output. The activation function such as Rectified Linear Unit (ReLU) and Sigmoid are used to generate the output. The Hybrid model classifies the tweets with greater accuracy.

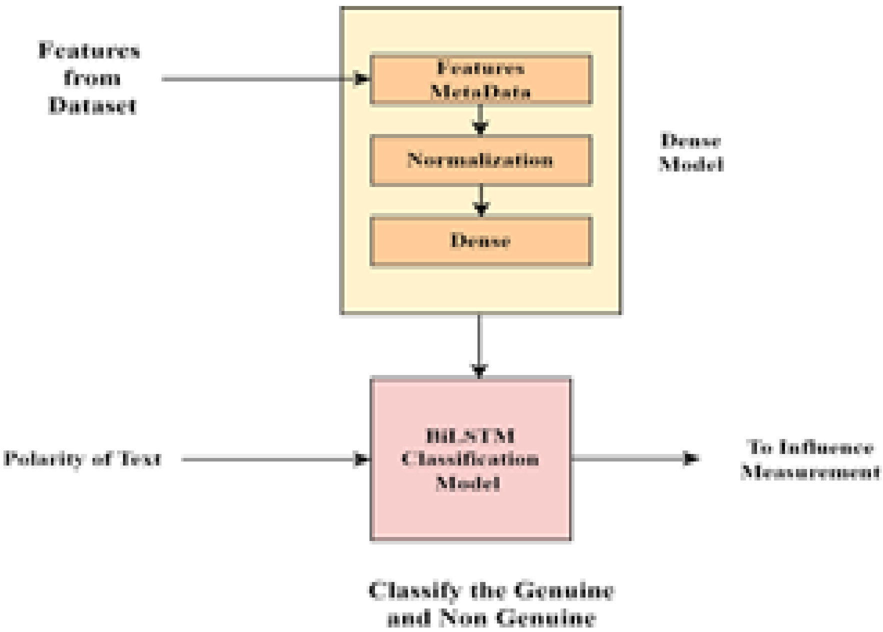

Figure 14: The Classification model for Genuineness of views

Algorithm for Genuineness of views

Begin

Step1. Tweet Extraction

Step2. For each Tweet do

Procedure Pre-process

Remove URL

Remove Hashtag

Remove usernames

Spell Check and correction

Replace Slangs

Replace Abbreviation

Remove Stop words

Lemmatization

Removal of Special Characters

End Procedure

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Step 3. Feature Extraction and Embedding

Step 4. Vectorization

Step 5.

```
Procedure Classification
        Classify each tweet using deep learning model
    If tweet is classified as neutral
        Classify tweet as neutral
    End If
    If tweet is classified as positive
        Classify tweet as positive
    End If
    If tweet is classified as negative
        Classify tweet as negative
    End If
    Write the classification Result to file
    End Procedure
```

Step 6.

```
Procedure Dense_Model
     Perform normalization and
             Dense
End Procedure
```

Step 7.

```
Procedure Classification
(Classification Result, Dense Model)
If the tweet is classify as Genuine
    Classify tweet as Genuine
End If
If the tweet is classified NonGenuine
    Classify tweet as NonGenuine
End If
    End Procedure
End
```

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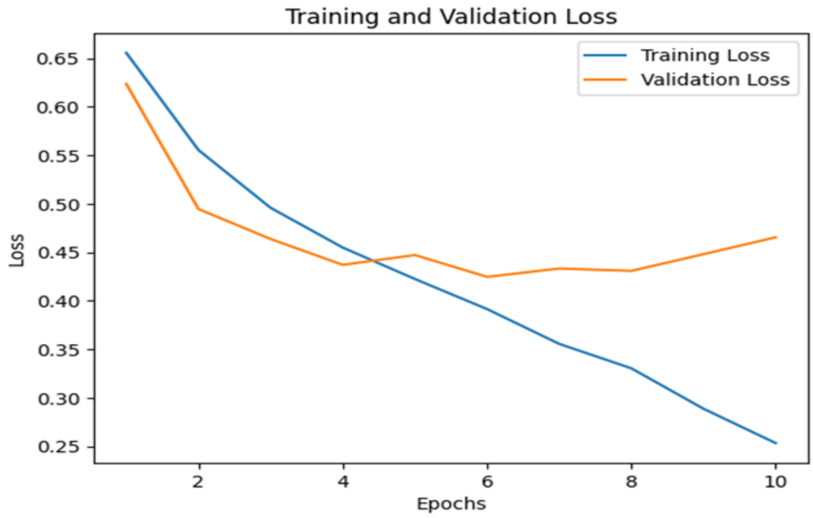

Figure 15:Training Loss versus Validation Loss

(For Genuineness of Views)

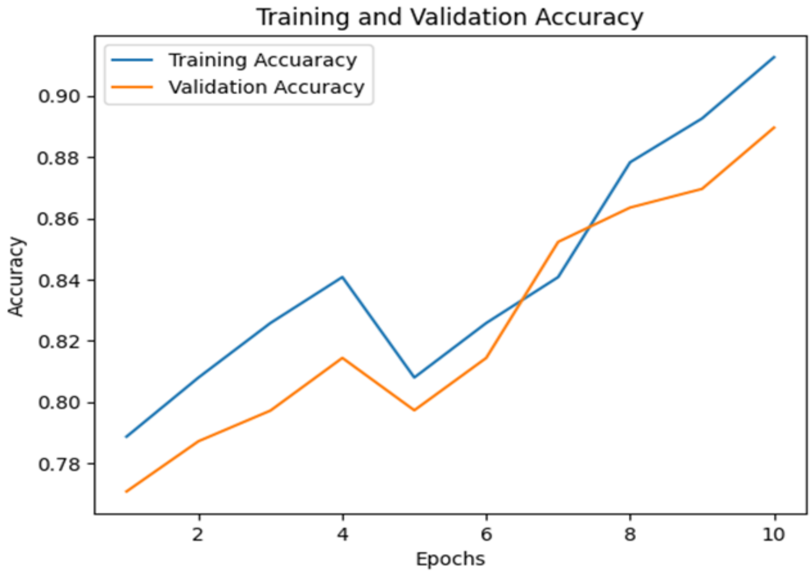

Figure 16: Training Accuracy versus Validation Accuracy

(For Genuineness of Views)

The Figure No.17 indicates the BiLSTM model Training and Validation loss for Sentiment Polarity. The model classifies the tweets up to the certain epochs. But models show over fitting after the certain number of epochs. Here in the Figure No.17 indicates that up to the certain epochs the model having less loss but as soon as the model over fits the loss increases and trend has been changes from ascending or descending. The validation and training curve shows the bias and tradeoff of the model.

Sr. No	No. of tweets	No. of Genuine Tweets	No. of NonGenuine Tweets
1	403182	342705 (85%)	60477 (15%)

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Evaluation Matrices

The accuracy of the model is dependent on several factors. The factors such as complexity of the problem, quality of data available for training and testing purpose , architecture of the model and the hyper parameters used and tuned while performing the training and testing. During the training of the model, loss function is important factor that calculates the difference between the predicted output and the actual output. So the primary goal of the training is to minimize the loss to improve the accuracy of the model. The other evaluation metrics for the classification task is recall, precision, accuracy and F1 score and confusion matrix.

Accuracy

Accuracy of the model is a measure of how often the model accurately predicts the outcome of the sample. It can be calculated by the ratio of the number of correctly predicted samples to the total number of samples in the datasets.

$$Acuracy = \frac{True\ Postive\ +\ TrueNegative}{Total\ Predicted}$$

Recall

Recall defined the proportion of true positive samples that are correctly classified out of all positive samples in the dataset. This is also known as sensitivity or True Positive Rate. Where True Positives are correctly classified as Positive out of total positive samples and False Negative are positive samples were not correctly identified by the model.

$$Recall = \frac{True\ Positive}{True\ Positive\ +False\ Negative}$$

Precision

Precision is an evaluation metric that measures the proportion of the true positive samples that are correctly identified by the model out of all the samples that the model identified as positive. It is also known as positive predictive value (PPV).

$$Precision = \frac{True\ Postive}{True\ Postive + False\ Postive}$$

Where true positives are the number of correctly identified positive samples and false positives are the number of negative samples that were incorrectly identified as positive by the model.

F1 Score

The F1 score is likely to be used for binary classification problems. It is evaluation metrics used to measure the performance of a classification model.F1 score is a harmonic mean of precision and recall. The range of the F1 score is between 0 and 1. The score is more, that indicates the model performance is better.

$$F1\,Score = 2 * ((Precision * Recall)/(Precision + Recall))$$

Confusion Matrix

The Confusion Matrix is a way to represent the evaluation of the model performance. It gives the summary related to the predicted class of model against to the actual or true class of a dataset. The matrix uses four various factors such as

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True Positive (TP)

True positive means, the model finds the correct which is predicted as positive.

False Positive (FP)

The model incorrectly predicted the positive class when the actual class is negative.

True Negative (TN): The model correctly predicted the negative class.

False Negative (FN): The model incorrectly predicted the negative class when the actual class is positive.

Classes	Real Positive	Real Negative
Positive Prediction	True Positive (TP)	False Positive (FP)
Negative Prediction	False Negative (FN)	True Negative (TN)

For implementation, various tools and techniques were used. These tools and techniques were implemented on the datasets. The tool Natural language Toolkit (NLTK) and spacy is used for the data transformation and applying natural language processing to datasets. The data which is collected from twitter is not in supervised form. To perform the experimentation, the supervised dataset is required. The collected data is converted into supervised form with the help of the Valence Aware Dictionary for sentiment Reasoning (VADER) which is Python based library for sentiment analysis.

Model for Influence Measurement

The tweets collected from Twitter are first preprocessed and converted to clean and non-errorious text. This text is then sent to the other module which calculates the polarity of the text. After obtained, the polarity of the text, the text is sent to another deep learning based model for Genuineness. Twitter Features used for Influence Measurement the tweets along with the various features are extracted from Twitter using TwitterAPI. All the collected tweets are processed by applying Natural language processing steps. This feature helps to measure the influence of the views shared by the user on twitter. The various features are given Table No.7.

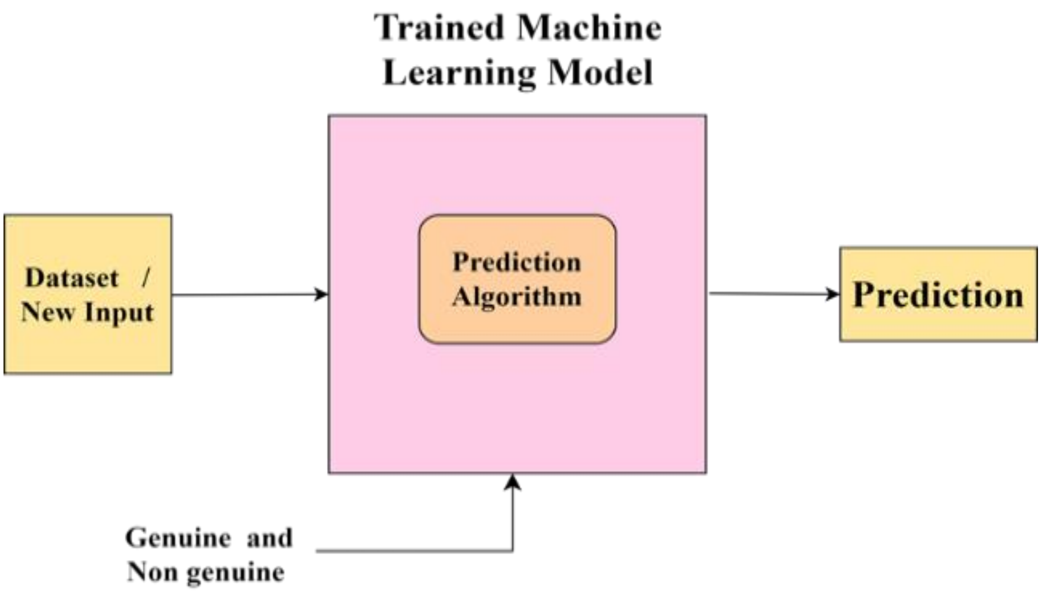

Figure 17: Machine Learning Model for Influence Measurement

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Table 4: Various Twitter Features used for Influence Measurement

Sr. No	Name of the Features
1	Text , Protected, Verified, Retweet ReplyCount, LikeCount, QuoteCount, Following_count, Followers_Count, Tweet_Count, Listed_Count, FriendsCount, Polarity, Genuine

Contribution of Features for Influence Measurement

The Figure No.20 Shows that the different tweet features contributed for the influence measurement. The total 12 tweet features are considered for the influence measurement. The graph shows that some features such as Followers Count, Friends Count, Listed Count, Like Count contribution are more and Retweet, Replay Count, Quote Count tweet features are contributed in less amount whereas the contribution of Protected and Verified features are negligible.

Some features of tweets are prominently contributed whereas contributions of some features are negligible. The extra tree classifier model is used for the prediction of the feature. This class uses Meta estimator that fits a number of randomized decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over fitting.

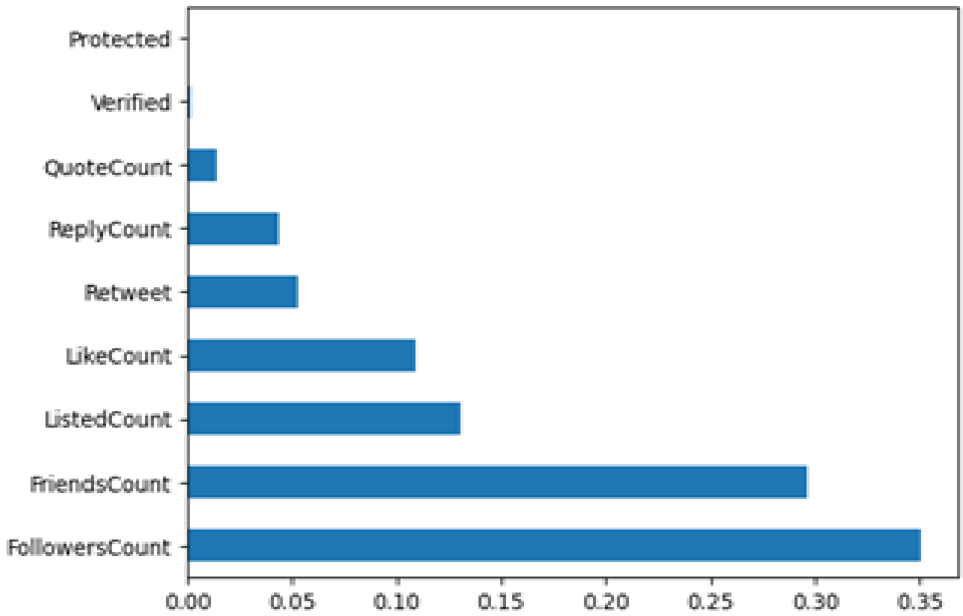

Figure 18: Contribution of Features in Influence Measurement

Table 5: Prominent and Negligible contributed Features

Sr. No.	Prominent contribution of Features	Negligible/Less contribution of Features
1	FollowersCount	Retweet
2	FriendsCount	ReplayCount
3	ListedCount	QuoteCount
4	LikeCount	Protected and Verified

The heat map of features shows in the Figure No.21.The heat map shows the dependency of features which are contributed.

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Performance Measures

The accuracy of the model is dependent on several factors. The factors such as complexity of the problem, the quality of data available for training and testing purpose , architecture of the model and the hyper parameters used and tuned while performing the training and testing.

During the training of the model, loss function is important factor that calculates the difference between the predicted output and the actual output. So the primary goal of the training is to minimize the loss to improve the accuracy of the model. The other evaluation metrics for the classification task is recall, precision, accuracy and F1 score and confusion matrix. For performance analysis various machine learning algorithms trained and tested. The performance of the varied machine learning algorithms are shown in the Table No.9.

RESULT AND DISCUSSION

The result of all models is shown in Table No.9.The performance of the model compare along with parameters such as accuracy, recall F1 score and Precision. The proposed Hybrid BiLSTM algorithm is significantly better than all the other methods in terms of accuracy, recall, F1 score and Precession. The proposed methods outperform the baseline methods in terms of accuracy, recall**,** F1 score and precision.

The proposed model design and implemented using hybrid approach by combining sentiment polarity and the features extracted from the tweets of the user. Most of the existing solutions used single textual information of tweet message. Although the studies happen recently shows that sentiment polarity is one most important factor for identification of genuineness or spam messages.

Figure 19: Heat map of features dependency

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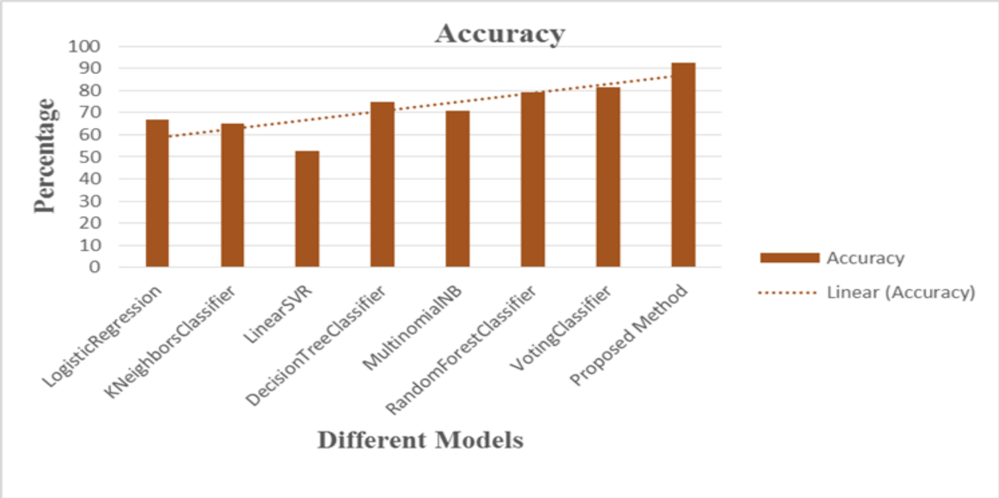

Figure 20: Performance of Model

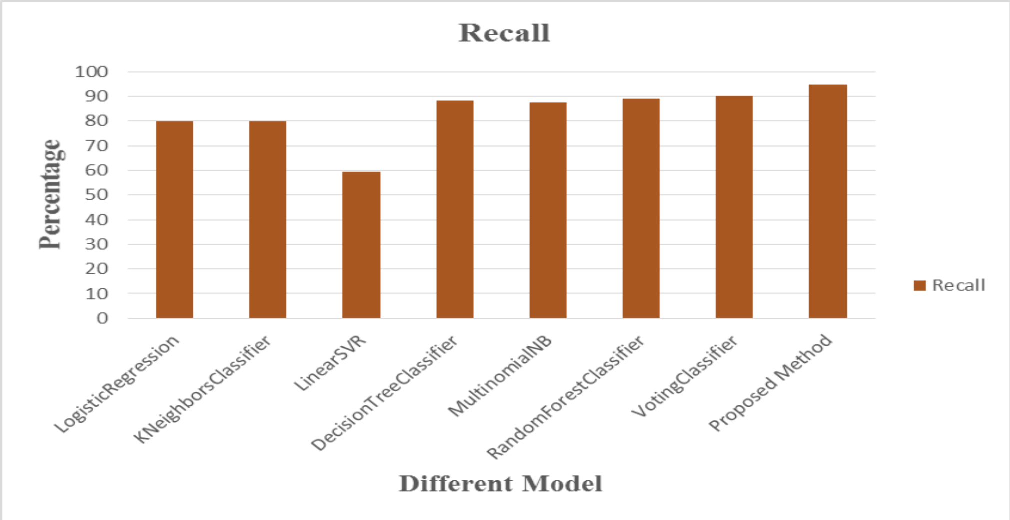

Figure 21: Performance of Model (Recall)

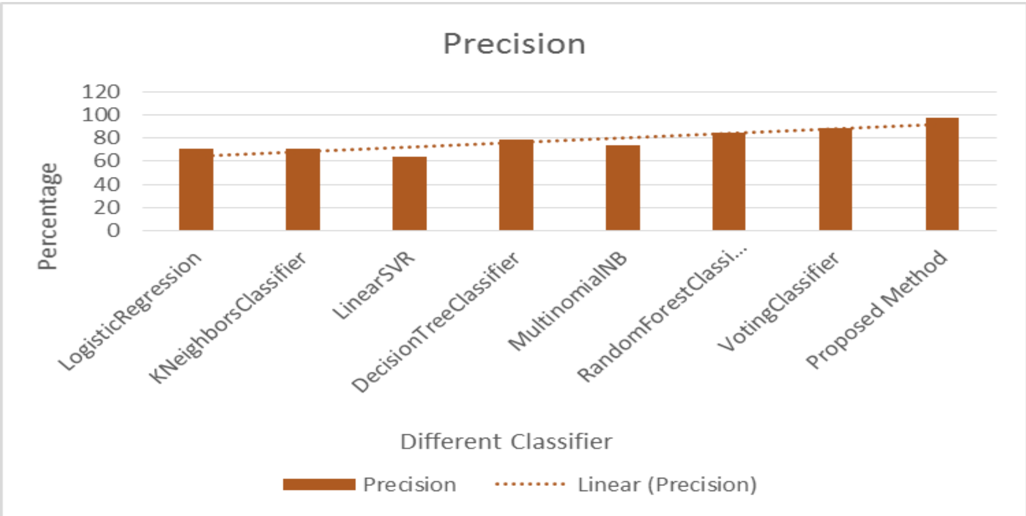

Figure 22: Performance of Model (Precision)

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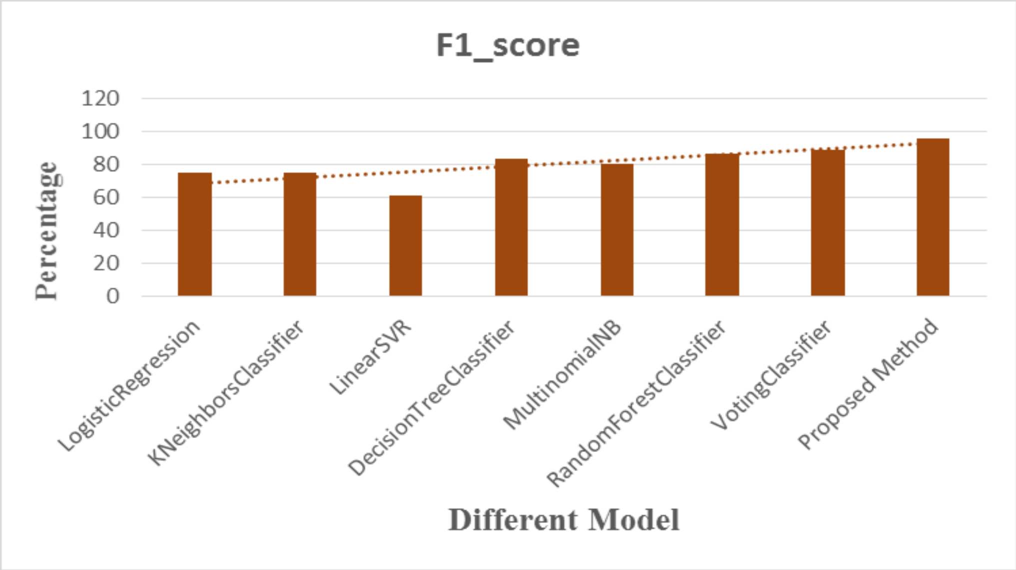

Figure 23: Performance of Model (F1_score)

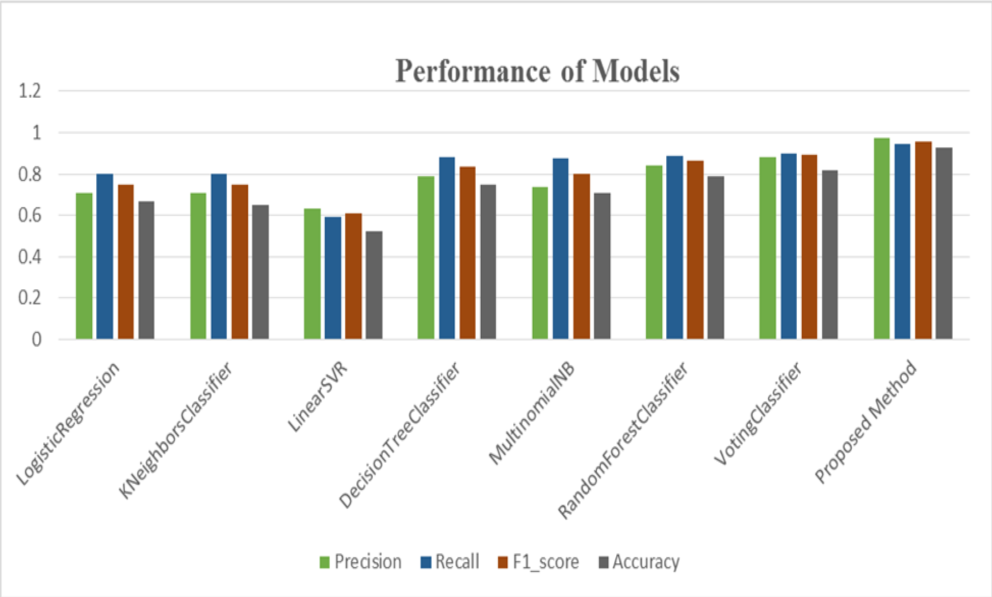

Figure 24: Different Model Performances

The dataset is designed and collected using the framework with the help of TwitterAPI V2.TwitterV2 API provides the various objects and its properties related to the Twitter messages. The designed framework of dataset collected using #Hash Tag e.g. #HDFC. The Natural Language Processing steps are applied to get the process data.

The proposed model had shown the better performance in case of accuracy, recall, F1 score and Precision. The measurement of the influence is depends on the features and properties that are contributed more.

The relation between the dependent variable and independent variables are shown in the Figure No.21.This Heatmap shows the relationship between the various features/properties and interdependency among them.

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Implication of Work

Sentiment analysis is offers the study and analysis of the opinion, attitudes, and any type of entity or product, organizations, individual, issue, and events. Online Social platform is most commonly used sites used in the today's world and peoples from the different corner of the world. Recently it is observed number of people actively involved in social media is rapidly increasing. As result of this there is tremendous amount of data is generated on internet. These valuable views shared by the user are used by the organization to determine the sentiments for many purposes.

Using sentiment analysis of valuable information, organizations build their decision-making model that will lead to the sale of a product and forecast future requirements. The number of views shared by the user on social media on particular product, service or any entity. The views shared by the user are not always legitimate. They are often spamming, illegitimate, fabricated, and fake. Due to the flow of such messages in social media, the connected user to social media are often get influenced by the polarity of the views. Many researchers worked on the spam detection, spam account detection, spam detection in Twitter etc.

This research was focused and aims to design an effective approach for genuineness of views using sentiment analysis and to measure the influence of views shared by the users on social media such as Twitter. Twitter is an online social media platform used by a lot of users for sharing the views regarding products, people and many types of services. These views are sometimes intentionally shared for making profits or to make someone at a loss. These views are mostly categorized into positive, negative or sometimes neutral. The implication of the research work:

a Using the Twitter views polarity of the text can be calculated to understand the sentiment. These sentiment polarities are useful to find the pattern and trends of users towards the particular product, people and services.

b Sentiment Polarity of the view and the various features of the views collected from Twitter combined for hybrid model development to identify the genuineness of the views.

c Using the genuineness of views and the features of views are then combined to measure the influence of the tweet. Furthermore it has been observed that, the various types of features of the views are played prominent role to measure the influence of the views.

d The user tweets or put any views on social media; some prominent information is attached with the user's views. This prominent information are very useful to predict and find the features contribution in measuring the influence of the tweet.

Comparative Analysis of Work

The various classifiers are used for comparison considering various performance measures. The various classifiers used the same dataset and various parameters. The proposed approach used the hybrid approach such as combination of features and polarity results the better accuracy than traditional classifier.

The hybrid model used word embedding using glove, a pre-trained word vector identify the semantic relationship between the various words present in the corpus. It also increases the computational efficiency as this word vector is pre-trained word vector. As a result, the proposed model outperforms the state of art machine learning and deep learning model.

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Table 5: Performance of Algorithms for Genuineness of Views

S.N	Classifier	Accuracy	Recall	F1 Score	Precision
1	Logistic Regression	70.59	72	65	66.67
2	K Nearest Neighbors	70.59	80	75	65.22
3	Linear SVR	63.39	59.21	61.23	52.5
4	Decision Tree Classifier	78.95	88.24	83.34	75
5	Multinomial Naive Bayes	73.68	87.5	82	85
6	Random Forest	84.21	88.89	85.36	79.17
7	Voting Classifier	88.24	90	86.25	81.67
8	BiLSTM (Hybrid Model)	95.22	94.59	93.89	92.5

Declaration Conflicts of interest/ Competing interests:

No conflicts of interest that could affect the objectivity or impartiality of this research.

Data Availability Statement:

Make available if asked.

Funding Sources:

This research did not receive any specific grant from any funding agencies.

Author's contributions

MRT conceptualized the study, performed the literature survey, and wrote the original draft of the manuscript. MRT, KHW and MA designed the experiment, synthesized the data and modeled interpretation, provided supervision and resources, and assisted in manuscript writing, review and editing. All authors approved the final manuscript version.

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