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Sentiment Analysis for E-Commerce Product Reviews Using Deep Learning

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ABSTRACT

Sentiment analysis (SA) is a process of extensive exploration of data stored on the web to identify and categorize the views expressed in a part of the text. In the sentiment classification, the accuracy or speed are difficulty to remove semantic ambiguity in sentiment analysis from the text ,but there are many machine learning that have a lot of similarities in features. Therefore, in this paper, we have expanded the sentiment into sentence analysis. We used deep learning model in natural language processing to analyse the sentence present in a given English language text, we used data on social media platforms such as Twitter. After working on processing the text and putting it in an understandable way for the classification model to find more efficient pre-processing techniques and more accurate and fast way to analyze sentiment from text, we used deep learning models by a recurrent neural network (RNN) with a state memory and multilayer cell structure Long Short-Term Memory (LSTM). We experimented and evaluated the method using Recurrent Neural Networks and Long short-term memory on dataset consists of a nearly 3000 Amazon customer reviews as input text , star ratings, date of review, variant and feedback of various amazon Alexa products for learning how to train learning for sentiment analysis, our use of this data to analyze Amazon Alexa product and API data; Discover insights into consumer reviews that are aided by deep learning models to achieve high emotion classification accuracy. A thorough evaluation shows that the system gains emotion prediction on LSTM model with 92.10 % accuracy for positive/negative classification with train time 25m for dataset and 93.18 % accuracy for positive and negative with train time 10s for API data.

Keywords: - Natural Language Processing (NLP); Sentiment Analysis; Twitter Platform ;Deep Learning Classifiers; RNN; LSTM.

I. INTRODUCTION

Natural Language Processing is a field that belongs to artificial intelligence, sentiment analysis recognition from text is crucial natural language processing (NLP) task which can contribute enormous benefits to different areas artificial intelligence. Which acts as an interface between humans and computers for interaction using various computational algorithms. Recent uses of NLP algorithms are spam mail detection, meeting report analysis, auto question answering, summarizing media reports, machine translation, and many more. Deep Learning is an postponement of machine learning and artificial intelligence that teaches computers to learn from experiences the same as humans do. Many deep learning models are successfully deployed for numerous natural language processing tasks for the last scarce years. Natural Language Processing (NLP) is originated from Artificial Intelligence It reads, deciphers, understands, and convert the human input in a valuable manner. It takes text data as input and converts it into more understandable structured data, easily analyzed and summarized. Using NLP algorithms, computers can read real-time data or listen from the audio source, understand it, and try to extract sentiment, feelings, and meanings associated with it recent human interaction with computers etc. Sentiment are physiologic thoughts engendered in human reactions to the events [1] .Sentiment analysis (SA) is a process of extensive survey of data stored on the Web to identify and categorize the views expressed in a part of the ext. The intended outcome of this process is to assess the author attitude toward a specific topic, movie, product, etc. The result is positive, negative, or neutral. These studies illustrated different techniques in SA approach for extracting and sentiments analyses associated with the polarity of positive, negative, or neutral on the topic selected. Social networks SA can be a useful source of information and data. SA acquires important in many areas of business, politics, and thought [2]. Analysis of these Sentiment without facial and voice inflection are critical and requires a supervisory approach for proper interpretation of sentiment. In spite of these challenges, it's essential to acknowledge the human sentiment as they progressively communicate using maltreatment text through social media applications such as Facebook, Twitter etc. Here, we use deep learning techniques to classify the sentiments of an expression into positive or negative sentiment. The positive sentiment is further classified into eagerness, fun, happiness, love, neutral, relief, surprise and negative sentiment are classified into anger, boredom, emptiness, hate, sadness, worry. We investigated and evaluated the method using Recurrent Neural Networks and Long short-term memory on three different datasets to show how to achieve high sentiment classification accuracy. Sentiment analysis is widely utilized by different parties such as shoppers or marketers to gain insights into merchandise or know the market trends [3]. Also, this is critical in predicting the exchange rate or the product rating of a selected organization. This is done by analysing the sentiment of the public towards the corporation with regard to time and positioning [4] .There is a need for a social science tool in order to understand the importance of public sentiments and thereby the market value of the enterprises. Firms can also estimate how well their product is moving in the market. Furthermore, it will help to analyze the positive and negative feedbacks about the products. This information will assist the corporation in analyzing different responses so that they can market their products in an optimized manner. The firms can also market their products using appropriate techniques, understand latest trends and develop market challenging products. The investigation of a numerical improvement made the application to change to the circle of AI (Artificial Intelligence).Data processing has a major role in research areas and in the field of study among AI. While considering its application across various businesses and research problems, AI is also considered as prognostic systematic [5]. During the last two decades, social media has become a big part of people's daily life. It is a communication channel where attitudes and opinions are shared and as such, it is a tool that shapes the future generation. Social networks open up the possibility for people everywhere to connect and make a difference and through that, it has the power to push instant change. Social media is an ideal platform to study these aspects thanks to the large amount of data that is available [6].

Therefore, in this paper, we proposed a deep learning model based on the use of Recurrent Neural Network (RNN) with a state memory and multilayer cell structure Long Short-Term Memory (LSTM) which can increase accurately and more efficient pre-processing techniques to remove ambiguity from the text. In addition to presentation of data that expresses text in a more understandable way.

The rest of this paper is organized as follows: the next Section 2 presents related works. In Section 3, we provide the materials and methodology. Section 4, presents the main results and discussion. Finally, Section 5 concludes this paper.

II. RELATED WORKS

Given the aim of this work, we recall some representative and related existing works to examine the posts to see if there is any relation between the future stock price and users' sentiment. In other words, we want to see if we can predict a future stock price based on the current sentiment of many users. For example, In [7]Zucco et.al illustrated different techniques in SA approach for extracting and analyses sentiments associated with the polarity of positive, negative, or neutral on the topic selected. Social networks SA can be a useful source of information and data. SA acquires important in many areas of business, politics, and thought. So, this study contains a comprehensive overview of the most important studies in this field from the past to the recent studies till. In [8], They review paper highlights latest studies regarding the implementation of deep learning models such as deep neural networks(RNN), convolutional neural networks(CNN) and many more for solving different problems of sentiment analysis such as sentiment classification, cross lingual problems, textual and visual analysis and product review analysis, etc. The authors showed full concept about SA techniques and its classification and methods used it. In [9], proposed a sentimental classification of multitude of tweets. Here, they used deep learning techniques to classify the sentiments of an expression into positive or negative sentiment. The positive sentiment are further classified into enthusiasm, fun, happiness, love, neutral, relief, surprise and negative sentiment are classified into anger, boredom, emptiness, hate, sadness, worry. They experimented and evaluated the method using Recurrent Neural Networks (RNN) and Long short-term memory (LSTM)on three different datasets to show how to achieve high emotion classification accuracy. A thorough evaluation shows that the system gains emotion prediction on LSTM model with 88.47% accuracy for positive/negative classification and 89.13% and 91.3% accuracy for positive and negative subclass respectively. In [10] based on the deep learning model, an improved sentiment on social networks, such as Twitter, has become a powerful means of learning about the users' opinions and has a wide range of applications. However, the efficiency and accuracy of sentiment analysis is being hindered by the challenges encountered in natural language processing (NLP). Deep learning models are promising solution to the challenges of NLP. In [11] The authors showed reviews the latest studies that have employed deep learning to solve sentiment analysis problems such as sentiment polarity. Models using term frequency-inverse document frequency (TF-IDF) and word embedding have been applied to a series of datasets. In [12], the study was proposed a sentiment analysis model-a SLCABG model for sentiment analysis on product reviews is constructed used sentiment dictionary, BERT model, CNN model, BiGRU model, and attention mechanism. The sentiment lexicon is used to enhance the sentiment features in the reviews. Then the CNN and GRU networks are used to extract the main sentimental and contextual features of the reviews, and attention mechanism is used to weight them, the weighted sentiment features are classified by analyzed the experimental results, it can be found that the model has better classification performance than other sentiment analysis models .They used model to analyze user review to help merchants on e-commerce platforms to obtain user feedback in time to improve their service quality and attract more customers to patronize. In[6] BERT-based models outperform the rule-based models VADER and TextBlob when it comes to precision, recall, and F1-score. Rule-based models add a bias in the classifications when using data collected with keywords due to the sentiment score of the keyword itself. More complex deep-learning models like BERT do not result in the same bias since it is based on context rather than rules.

By adding a more comprehensive filter to Twitter API the data could be more suitable for the analysis. This could decrease the amount of noise and outliers in the dataset. In all of the different SDGs, the majority of tweets were positive and all had a similar pattern in the distribution. Most of the keywords had between 60-70% positive tweets. In[13], authors focused on the basics of sentiment /opinion mining and its levels. There are various approaches and methods to identify sentiment from content. They examined represents machine learning procedures. From various classification methods, Sentiment Analysis indicates the results into positive, negative and neutral scores. They showed that machine learning methods, such as SVM, Naive Bayes, and neural networks had the highest accuracy and can be considered as the baseline learning methods as well as in some cases lexicon based methods are very effective. Neural network and deep learning shows more accuracy than usual machine learning algorithms. They recommended in future work and discovering the result of various other combinations of text data and other on prediction accuracy can be done. In addition to more work in the future is needed to advance performance measures.

From the presented related works, there are many studies that have classified sentiment focused one aspect of the analysis sentiment analysis paradigms , we can conclude that obtaining high accuracy in the classification. Hence, the comparison of our proposed model and the state-of-the-art proved the validity and efficiency of our proposed model which exceeds all proposed models' results and demonstrated its robustness in coping with the limited availability of training data. In fact, in the sentiment classification, the accuracy or speed are difficulty to remove semantic ambiguity in sentiment analysis from the text. but there are many machine learning that have a lot of similarities in features. Therefore, in this paper, we have expand the sentiment into sentence analysis. We used more efficient pre-processing techniques and find a more accurate and fast way to analyse sentiment from text, we are using deep learning models by a recurrent neural network (RNN) with a state memory and multilayer cell structure Long Short-Term Memory (LSTM).

III. MATERIALS AND METHODS

In this paper, we used deep learning models in natural language processing to analyse the emotion present in a given English language text. Using data on social media platforms such as Twitter. After working on processing the text and putting it in an understandable way for the classification model.

In this section, the sentiment analysis methodology differs according to the need for the results and their accuracy .Five main steps, ranging from the place of data collection as texts to the appearance of the results will be introduced (See Figure 1). In the rest of this Section, we describe the main datasets, the employed deep learning techniques, as well as performance evaluation of the proposed model.

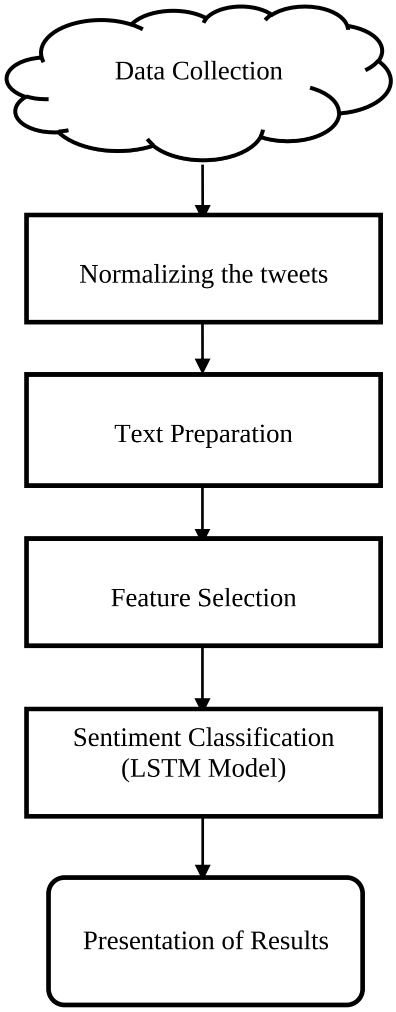

Fig .1 The five steps of sentiment analysis

1) Data Collection

Though data sets for the experiments are widely available across various social networking platforms, the manual determination of sentiments of different tweets is a challenging task. It requires a high level of expertise in the area to perform a vigilant analysis of these tweets and generate accurate results. Existing public datasets having URL are rather limited due to these challenges.

This dataset consists of a nearly 3150 Amazon customer reviews (input text), star ratings, date of review, variant and feedback of various amazon Alexa products like Alexa Echo, Echo dots, Alexa Firesticks etc. for learning how to train Machine for sentiment analysis, our use of this data to analyse your Amazon Alexa product; Discover insights into consumer reviews that are aided by deep learning models. In Features of dataset descriptions of the features that were utilized to generate the data sets are provided below, each row of the log contains the information. In Table 1 we provide a description of the newly created dataset, and in Figure 3 samples of the dataset are depicted.

Table.1 Description of the Features of dataset

Index	Rating	Date	Variation	Verified_reviews	Feedback
1	5	29-Jul-18	Charcoal Fabric	Love my Echo!	1
2	5	29-Jul-18	Charcoal Fabric	Loved it!	1
3	4	29-Jul-18	Walnut Finish	"Sometimes while playing a game, yo…	1
4	5	29-Jul-18	Charcoal Fabric	"I have had a lot of fun with this thing…	1
5	5	29-Jul-18	Charcoal Fabric	Music	1
6	5	29-Jul-18	Heather Gray...	"I received the echo as a gift. I neede...	1
7	3	29-Jul-18	Sandstone Fabric	"Without having a cellphone, I canno...	1
8	5	29-Jul-18	Charcoal Fabric	I think this is the 5th one I've purchas...	1
9	5	29-Jul-18	Heather Gray...	looks great	1
10	5	29-Jul-18	Heather Gray...	"Love it! I've listened to songs I have…	1
...	..	…	…	…	…
3148	5	29-Jul-18	Black Dot	"I do love these things, i have them ..	1
3149	5	29-Jul-18	White Dot	"Only complaint I have is that the…	1
3150	4	29-Jul-18	Black Dot	Good	1

Normalizing tweets makes the data suitable for pre-processing. Pre-processing steps are mandatory to avoid spam codes and get tweets in a natural way, which in turn defines the data that needs to be handled and configured for the pre-processing process.

2) Text preparation

Text preparation examines the data before analysing it. Some reviews and conversations in the communication sites contain offensive and inappropriate words, so they are examined and preparation to be the result more reliable analysis. This process selects the contents that are not related to the analysis and then removes it. Objective of the process is the removal of spam and inappropriate reviews before sent to automated analysis. We are using NLTK techniques.

3) Pre-processing

The messages from Twitter are too informal and has different styles of using tweets based on the nationality, origin, age and the gender of the user. Therefore, tweets taken from twitter generally result in a noisy data set of unwanted emoticons and symbols. Twitter users will use different kinds of special characters like sending the tweets again, which are termed as re-tweets, emoticons, personalized wording etc. all of which are to be suitably extracted. Hence for creating new datasets, raw twitter data has to be normalized for easiness of the classifier algorithms to perform the emotion analysis. There are different pre-processing methods available for tweets[2] .

The main reason for using the pre-processing task is to reduce the noise and size of the messages. Initially we perform few general and mandatory pre-processing task which include conversion of words to lower case. Also, there are tweets with more dots as we use informal conversation. So, the additional dot is replaced with a space. At the end, we remove unwanted space and special characters. Multiple spaces can be avoided by replacing them with a single space. The URL from the twitter messages will not be used in the analysis as it leads to a sparse result. Hence, we replaced all the URL in the tweets with the expression ((www\. [\S] +))) . Handle is another special character used in tweets to mention other user names in their messages. The users commonly use the tagging of another user as @name_user.

As we are eliminating all unwanted symbols from the data sets, we replace all user tagging like the @name_user with the word USER-MENTION. The equivalent expression used to match user tagging is @[\s] +.2. It is very common to use different types of images in the tweets. These include smiley symbols, hand gestures, etc. Since the social media sites have a wide range of such images, it is very difficult to find equivalent expression for each among them.

However, we cannot exclude the text as they play a major role in the emotion transfer and therefore, we use two types of substitutions for positive and negative sentiment as emoj-positive and emoj-negative respectively. Hashtags are used to categorize tweets and messages on similar or common area so that people can easily find the area of interest. They are phrases without any space and preceded by a # symbol. When we click on the hashtags it will move to other tweets that also have the same hashtag. So, these are from the same area of interest. For replacing and giving a common format for these hashtags, we will remove the hash symbol and replace the hashtag with the word which comes after the hash symbol. The regular expression used to match the hashtag is # (+).

It is common to resend the tweets which we have already received from other users for many reasons. This gives more flexibility to the use of tweets and make this platform more interesting. Normally these retweets begin with the letter RT and during the pre-processing phase these RT will be removed as it is not relevant for the classification of tweet sentiment. The retweets are represented as \brt\b. After the pre-processing of the URL, Hashtags and retweets, the main part of tweet processing is the clearing of punctuations in the tweets. That is, in a tweet message like "Oh my God!! I cannot believe this."

we will remove the punctuation and rephrase the tweets. For getting better features for the classification we need to remove all the punctuation, like’’‘! ()-[]{};:’"\, <>. ? @%ˆ* ’’’ /.

Twitter is a platform where users can convey their feelings through different expressions. Many people will post tweets like “I am sooooo surprised” to highlight their sentiment. But during the word level processing of tweets we must ignore these duplications. The other word level processing includes the removal of “-” and “’” which is commonly used in typing t-shirts and can’t. These are represented as ”tshirt” and ”can”t in a more generalized manner [2] .

4) Features Selection

In features selection we used Term Frequency Inverse Document Frequency (TF-IDF) is used in natural language processing for identifying the important words or rare words in a text data. Term frequency converts the words that are in string format for numerical formatted data so that the machine learning models can understand the information. Term Frequency TF is used to find out the frequency of occurrence of words that we have for the classes. In our data set the feature is words. The frequency of each word in the dataset which is being calculated using term frequency.

$$TF(I,j) = \frac{term\ i\ frequency\ in\ document\ j}{total\ words\ in\ doc\ j}$$

IDF helps us to take meaningful words from the document. TF gives us the highest degree words while IDF helps us to get the lowest occurred words by taking the logarithm of the values.

$$IDF(i) = \log 2\left(\frac{(total\ number\ of\ documents)}{(number\ of\ documents\ with\ term\ i)}\right)$$

We find that the product of both the TF and IDF matrices is the normalized weights which is the TF-IDF output. In this way we get the numerical input for the machine learning model. TF-IDF is used to represent text with a BoW (Bag of Words). Converting the Reviews into Numerical Vectors (doc2vec).

The doc2vec vector algorithm performs considerably well for sentence similarity tasks. However, if the input corpus includes a lot of words with misspellings like tweets, this algorithm may not be an ideal choice. We used Doc2Vec method which is used for the vectorization of documents. This is an improved version of Word2Vec. This method was not desirable in the works where a lot of misspellings of words occur. It is better to convert words to vectors and then use these vectors to create the vector format of the whole document. Doc2Vec is used to represent text with word vectors.

Train-Test Split Date ,One of the golden rules in deep learning is to split your dataset into train, validation, and test set. The reason we do that is very simple. If we would not split the data into different sets the model would be evaluated on the same data it has seen during training, Back before using deep learning models we often used two different sets. A train set is used for training the model, A test set that is used to evaluate the final model accuracy before deployment.

5) Sentiment Classification by LSTM model Constructor

LSTM helps us to classify our tweets by also using the long range of dependencies. The LSTM has flexibility to get rid of or append information to the cell which keeps track of the sate information, and these are controlled by gates. Gates allow the information to pass through the network. The segment layer has the outputs range between 1 and 0 which denotes the information which are passing through. If the obtained value is 0, it tells us that nothing is passing through the gate and a value of 1 describes that everything can be pass through. Initially, we have to identify the features to be fed to the cell state. The forget layer in the LSTM architecture is responsible for this decision whether to forget or accept the features. By considering the value of ht-1 and xt it will give two values as output. That is, the output values can either be a 0 or a 1 for each cell state. If the value is 1, it represents the acceptance of the feature and 0 represents the avoidance of the information. In this work we must accept or reject the feature words from the data sets to classify the emotion. In each cell state, the new emotion word has to be accepted or rejected based on the emotion of the tweets (See Figure 2).

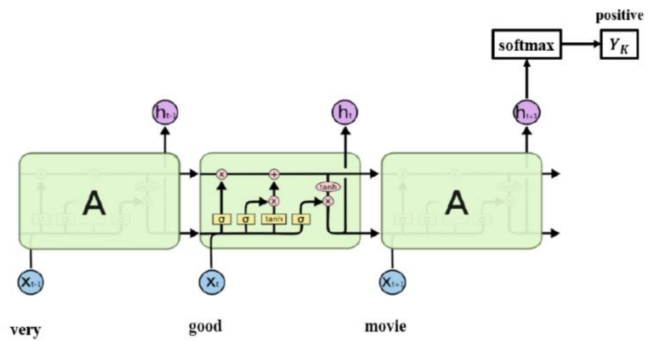

Fig .2 LSTM model constructor

Test cases for positive and negative emotions are demonstrated here with an example.

Case 1: Positive:

For example: “omg!!! It is surprising,” it is categorized as positive. Further, it is categorized based on the percentage in correspondence to each emotion. Here we get 40.91% for surprise, 28.27% of relief, 11.64% for fun, 7.22% of neutral and less than 5 percentage for another three emotions each, which shows that the emotion surprise is more dominant in this comment. Hence it is categorized as a surprise.

Case 2: Negative:

For example: “I am so panic these days”, it is categorized as negative emotion statement. Further, it is categorized based on the percentage of correspondence to each emotion. Here we get 78.43 percentage to worry, only 14.82% is for sadness, 5.49% of empty and other three emotions together obtain only 1.26% of the total. So, it is categorized as worry.

Model Accuracy

In the measurement of accuracy, there have chances of miss interpretation of the prediction.

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

That is, the actual defected results are being identified as true cases and is termed as True Positive, represented as TN. Also, some cases which are correct are being recognized as negative, called as False positive and is represented as FP.

Presentation of Output

The main objective of analysing a huge amount of data is to convert unstructured text into useful information and then to display it through charts such as a graph, line graph, and bar graph [5].

Performance Evaluation of the Model

In this phase, performance evaluation will be builder the LSTM model used the 'Keras' library. This step involves model initialization, adding required LSTM layers, and model compilation. Hence, in the measurement of accuracy, there have chances of miss interpretation of the prediction. That is, the actual defected results are being identified as true cases and is termed as True Positive, represented as TN. Also, some cases which are correct are being recognized as negative, called as False positive and is represented as FP, we have to calculate the following metrics for the test rating.

- True Positive (TP): Refers to the number of predictions where the classifier correctly predicts the positive category as positive.
- True Negative (TN): Refers to the number of predictions where the classifier correctly predicts the negative category as negative.
- False Positive (FP): Refers to the number of predictions where the classifier incorrectly predicts the negative class as positive.
- False Negative (FN): Refers to the number of predictions where the classifier incorrectly predicts the positive class as negative.

Before using deep learning models, we often used two different sets. A train set is used for training the model and a test set that is used to evaluate the final model accuracy before deployment.

6) RESULTS AND DISCUSSION

Python programming language and Keras packages were used to train the proposed deep transfer learning models. It is contains libraries of artificial intelligence models and ready-made classification methods. And Jupyter notebook is the latest web-based interactive development environment for notebooks, code, and data. Its flexible interface allows users to configure and arrange workflows in data science. API were used to collected information from the source and sends it to the classification model. All experiments were performed on Twitter represents a data source and contains a specific text format that enables easy text classification.

To analyze sentiment from sentence, we need many tools. These tools are divided between tools for collecting data from the data source, tools for processing sentence before the classification process, and classification tools that represent functions from a programming language that enables analysing and extracting sentiment from the sentence. We present the experimental results and used the LSTM (Long-Short Term Memory) algorithm to classify the emotions from the text (positive or negative) after training the model on the training data and testing the model with the test data. The experimental steps were a dataset loading the dataset and creating a new column 'sentiment' based on 'rating'. This dataset encoded the target variable with a 2-point ordinal scale: 0 = negative, 1 = positive.

We are building the LSTM model are depicted in Figure.4 using the 'Keras' library. This step involves model initialization, adding required LSTM layers, and model compilation.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 10, 50)            225750

 lstm (LSTM)                 (None, 10, 50)            20200

 lstm_1 (LSTM)               (None, 10)                2440

 dropout (Dropout)           (None, 10)                0

 dense (Dense)               (None, 8)                 88

 dense_1 (Dense)             (None, 1)                 9

=================================================================
Total params: 248,487
Trainable params: 248,487
Non-trainable params: 0
```

Fig .3 Model Design

We can see that the training the model using train data are depicted in Figure5 and Figure6 .The train-test split procedure is used to estimate the performance of deep learning LSTM Model when they are used to make predictions on data not used to train the model.

```
Output exceeds the size limit. Open the full output data in a text editor
Epoch 1/5
89/89 - 1s - loss: 0.2144 - accuracy: 0.9182 - 1s/epoch - 16ms/step
Epoch 2/5
89/89 - 2s - loss: 0.2091 - accuracy: 0.9189 - 2s/epoch - 18ms/step
Epoch 3/5
...
Epoch 4/5
89/89 - 2s - loss: 0.1986 - accuracy: 0.9203 - 2s/epoch - 17ms/step
Epoch 5/5
89/89 - 1s - loss: 0.1914 - accuracy: 0.9196 - 1s/epoch - 16ms/step
```

Fig .4 Training the model

Fig .5 Training-Testing Accuracy

Save the model allows to save your model to file and load it later in order to make predictions. We use predictions model by new data to obtain actual data to test the model's work on any other data, we obtain that through the API, data marked with (hashtags) from Twitter.

Fig .6 Results Of Predictions

Results of model is content of accuracy and loss of dataset for new API data from twitter and execute time. The final result of the model prediction for API data are depicted in Table 2.

Table .2 Performance measurements for all models

Number of layers	**Data**	**Accuracy**	**Loss**	**Train time**
5	Data Set	0.9210	0.079	25m
	API Data	0.9318	0.0682	10s

In[9] the authors present modeled a system for sentiment analysis of twitter messages. The tweets we consider in the analysis are, a mixture of different words and emoticons. We modeled the classifier With deep learning techniques such as RNN and LSTM. In order to gain better accuracy, we incorporated different feature selection methods like TF-IDF and Doc2Vect. The feature extraction generates a vector that is been given as input to the classification model. Our model achieved better results in the task of classifying the twitter emotional messages. As a future work, the analysis of the personality of the users from their tweets are need to be investigated, so that the system can be more personalized.

IV. CONCLUSION & FUTURE SCOPE

In this paper, a deep learning model based on transfer learning is proposed used the LSTM (Long- Short Term Memory) algorithm to efficiently classify the emotions from the text (positive or negative) after training the model on the training data and testing the model with the test data. We found that the LSTM model gives more accurate results in classification, the greater the number of data used in training, and the greater the number of layers of the model structure, the more accurate the model in classification, and that is inversely proportional to the training time and loss data. Evaluation of the model shows that the system gains emotion prediction on LSTM model with 92.10 % accuracy for positive/negative classification with train time 25m for dataset and 93.18 % accuracy for positive and negative with train time 10s for API data. In future work, we recommend to combine LSTM to get less execution time with the layers for large twitter datasets.

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