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SENTIMENT ANALYSIS BASED TWITTER TWEETS CLASSIFICATION USING DATA EMBEDDED WITH LSTM TECHNIQUE

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ABSTRACT

Over the last two decades, social media sites have established themselves into our regular lifestyle. Collecting information from social media, following trends in social media, and knowing about people's feelings and emotions on social media are all very important today. Twitter sentiment analysis is an application of sentiment analysis on data from Twitter (tweets), in order to extract sentiments conveyed by the user. Twitter emotion recognition has gained a lot of attention nowadays due to its numerous uses in the business and government sectors. It is possible to conduct many analyses using this source. One of the most essential of these analytics, sentiment analysis, is gaining popularity. Real-time messaging and opinion sharing in social media websites have made them valuable sources of different kinds of information. Sentiment analysis attempts to extract beliefs, attitudes, and feelings from social media platforms like twitter. On the other hand, Deep Learning (DL) approaches have been increasingly popular among researchers in recent years and offer solutions to a wide range issues. However, there is a need to explore the efficacy of real-time systems that includes popular and real-time focused tweets. Hence in this approach, Sentiment analysis based twitter tweets classification using data embedded with LSTM technique. The LSTM networks and convolutional Neural Networks have shown to be effective for sentiment analysis applications. In this analysis, Long Short-Term Memory (LSTM) method is used to evaluate a tweet's emotional content. This presented approach will achieve better results in terms of Accuracy, Precision and True Positive Rate (TPR).

KEYWORDS: *Sentiment Analysis, Deep Learning, Twitter, Long Short-Term Memory, Valence Aware Dictionary for sEntiment Reasoner (VADER).*

1. INTRODUCTION

The semantic web, Artificial Intelligence, connectivity, and other key components of Web 3.0 enable users to use social media to connect and share their perspectives about current events [1]. Social media websites have become useful sources of different kinds of data due to real-time messaging and opinion exchanging. Social media has recently gained popularity as a means of disseminating information around the world or universe. Users can upload and share different types of multimodal text in a social setting using social media without having much knowledge of the Web's client-server architecture or network topology. Social media websites have grown in popularity as a method of exchanging thoughts and opinions on a wide range of topics. People use social media to share their thoughts on many topics, discuss recent news, and express their feelings [5]. They exchange information through Facebook, Twitter, and other social media applications, but they also comment on the information to express their feelings about it, whether positive or negative. One of the most popular social media platforms for micro blogging, Twitter enables users to share information in real time on a range of topics and events. Sentiment analysis is one of the many essential analytical activities that can be performed

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using the platform's enormous volumes of micro blogging data [6]. Using succinct 140-character messages known as "tweets," users are now likely to spread information on various features of Twitter. Additionally, they follow other users in order to get their twitter status updates. People use Twitter as a popular instant messaging service to stay informed about current events, such as worldwide news and advances in science.

Sentiment analysis attempts to gather beliefs, attitudes, and feelings from social media platforms like twitter. It has become more popular as a research area. The typical method of sentiment analysis places the greatest emphasis on textual data. The most well-known micro blogging social networking site is Twitter, where users send updates about various topics as tweets [9]. This analysis's ultimate purpose is to understanding the emotional orientation toward entities such as products, organizations, individuals, events, issues, or topics.

Due to the substantial development and popularization of Twitter as a platform for citizens to share their ideas and attitudes on a wide range of topics, Twitter sentiment analysis has drawn a lot of attention. Twitter sentiment analysis allows us to keep track of reviews of services and product reviews on social media and it may help to detect negative mentions and angry customers. Twitter sentiment classification, which determines the polarity of a tweet's sentiment, has gained much attention in the field of natural language processing. Individuals, businesses, and governments all benefit from it because they want to understand people's viewpoints on various products and policies. In order to extract emotional expressions from text messages (tweets) on Twitter, complex techniques for sentiment text analysis are typically implemented. These techniques can be divided into three categories: positive, negative, and neutral. This role also provide analyzing opinions, dialogues, announcements, and news (within a single thread of tweets) in order to develop business strategies, political analyses, and assessments of public action, among other things [4].

The automatic technique of text sentiment analysis can evaluate the sentiment polarity of a text segment as well as whether it contains objective or subjective content. To automatically evaluate whether a tweet has a positive or negative emotion, Twitter uses sentiment categorization. Numerous techniques for extracting useful features and classifying text into appropriate polarity labels are based on various approaches to natural language processing and Machine Learning. The simplest sentiment classification results were obtained utilizing Machine Learning (ML) supervised learning techniques such as Naive Bayes and Support Vector Machines, but the manual labeling required for the supervised approach is incredibly expensive. There has been some work done on unsupervised and semi-supervised techniques, and there is still much room for improvement.

The reason behind this is the challenging format of the tweets which makes the processing difficult. The tweet format is very small which generates a whole new dimension of problems like use of slang, abbreviations etc. A lot of research has been done on Twitter data in order to classify the tweets and analyze the results. However, due to the presence of non-useful characters (collectively termed as noise) along with useful data, it becomes difficult to implement models on them. On the other hand, With the popularity of deep learning techniques in recent years, different deep neural networks have been successfully used in the field. [12]. Deep learning techniques have achieved outstanding results in numerous natural language processing applications, including sentiment analysis, in recent years. The LSTM networks and convolutional Neural Networks in particular showed to be effective for sentiment analysis applications. Hence in this approach, sentiment analysis based twitter tweets classification using data embedded with LSTM technique.

The remaining of the content is organized in the following manner: The research on Twitter sentiment analysis is described in section II. The section III demonstrates the sentiment analysis based twitter tweets classification using data embedded with LSTM technique. The section IV describes the result analysis of presented approach. Section V presents the work to a conclusion.

2. LITEARATURE SURVEY

Zhao Jianqiang, Gui Xiaolin and Zhang Xuejun et. al. [14] for sentiment analysis, Twitter provides deep convolution neural networks. In this methodology, a word embedding method that uses latent contextual semantic linkages and co-occurrence statistical features between words in tweets is described. For training and predicting sentiment classifications labels, the feature set is integrated into a deep convolution neural network. On five Twitter data sets, the effectiveness of this model was experimentally compared with the baseline model, the term n-grams model. The results show that the described model is more appropriate on accuracy and the F1-measure for classifying Twitter sentiment.

Yusuf Arslan, Aysenur Birturk, Bekjan Djumabaev, Dilek Kucuk et. al. [15] offers Real-Time Lexicon-Based Sentiment Analysis Experiments on Twitter with A Mild (More Information, Less Data) Approach. The authors utilized different sentiment analysis approaches, including dynamic dictionaries and models, and performed tests on limited but relevant datasets to understand the popularity of some terms and user perceptions of them. These experiments have produced promising results.

Yafeng Ren, Meishan Zhang Yue Zhang, and Donghong Ji et. al. [17] utilizes a neural network to provide context-sensitive Twitter sentiment classification. A context-based neural network model for Twitter sentiment analysis that integrates contextualized data from relevant Tweets as word embedding vectors into the model The experimental results demonstrated that our proposed context-based model performs better the state-of-start discrete and continuous word representation models, proving the efficacy of the context-based neural network model for this task. Additionally, the authors discovered that topic-based contextual features are the most successful in context-based neural network settings.

Hassan Saif, Yulan He, Miriam Fernandez, Harith Alani et. al. [19] Contextual semantics is made available for Twitter sentiment analysis. This method can detect sentiment at both the entity and tweet levels. Utilizing three alternative sentiment lexicons to infer pre-word sentiments, the presented technique is tested on three Twitter datasets. Our approach outperforms the baselines in terms of accuracy and F-measure for entity-level subjectivity (neutral vs. polar) and polarity (positive vs. negative) detections. On two out of three datasets for tweet-level sentiment identification, this method outperformed the most recent lexicon-based method Senti-Strength in terms of overall performance.

Monisha Kanakaraj, Ram Mohana Reddy Guddeti et. al. [20] explains sentiment analysis based on NLP utilising ensemble classifiers using Twitter data. They describe a Natural Language Processing (NLP)-based technique to enhancing sentiment classification by including semantics into feature vectors and thereby utilizing ensemble methods for classifications. Prediction accuracy is increased by enhancing feature vectors with context-sense identities and semantically related words. According to analyses, the semantics based feature vector with ensemble classification performs 3–5% better than the conventional bag-of-words technique with a single machine learning method.

However, the existing simple approaches are statistical, based on the frequency of positive and negative words. Recent advances accounting for additional content features have been made by researchers. But there are still difficulties in this area of research. To overcome these challenges and to develop an effective approach, sentiment analysis based twitter tweets classification using data embedded with LSTM technique is presented.

3. SENTIMENT ANALYSIS BASED TWITTER TWEETS CLASSIFICATION

In this section, sentiment analysis based twitter tweets using data embedded with LSTM technique is presented. Fig. 1 shows the work flow diagram of the presented technique.

In this approach, different types of tweets are collected in real time to classify the sentiments in those tweets. A tweet is a micro blog message that is posted on Twitter. There are only 140 characters allowed. The majority of tweets are text-based with integrated URLs, images, usernames, and emoticons. There are also mistakes in papers. As a result, a series of preprocessing processes are performed to remove unnecessary information from tweets.

Pre-processing: Raw tweets from Twitter that are collected typically produce a noisy dataset. This is a result of people using social media in a casual manner. Retweets, emoticons, user mentions and other unique aspects of tweets must be appropriately retrieved. Therefore, normalizing the raw Twitter data is necessary to provide a dataset that can be quickly trained by different classifiers. The dataset is standardized and its size is decreased using a large number of pre-processing procedures.

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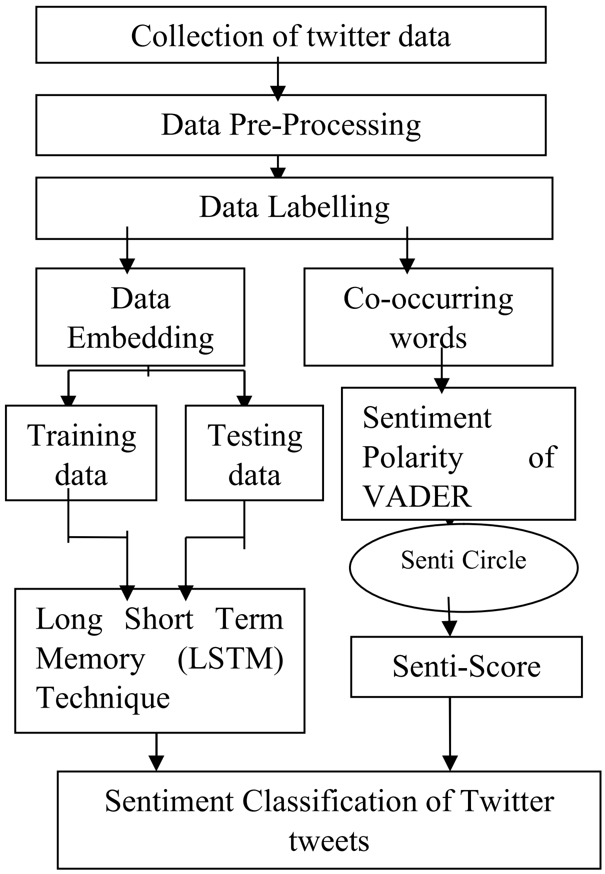

Fig. 1: Workflow Diagram of Sentiment Analysis Based Twitter Tweets Classification

First, some general pre-processing of tweets is performed, as shown below.
I Change the tweet's case to lower case.
ii) 2 or more dots (.) should be replaced with spaces.
iii) Remove all spaces and quotations (" and ') from the end of the tweet.
iv) Replace a single space for two or more spaces.
The following are the special Twitter features.

URL (Uniform Resource Locator): In their tweets, users frequently include links to other websites. Given that it leads to a relatively limited number of attributes, any specific URL is not significant for text classification. As a result, it will return every URL found in tweets containing the word URL. URLs are matched using the design pattern ((www.[\S]+)|(https?://[S]+)).

User Mention: Each and every Twitter user has a unique handle. Other users are frequently mentioned in tweets by @handle. All user mentions are changed to USER MENTION. @[\S]+ is the regular expression that is used to match user mention.

Emoticon: In order to portray a wide range of feelings in a tweet, users generally utilize a variety of different emoticons. Since there are so many distinct emoticons being used on social media, it is impossible to match them all completely. However, it is possible to match several widely used common emoticons. Depending on whether the matched emoticons are expressing a positive or negative feeling, EMO_POS (EMOtion POSitive) or EMO_NEG (EMOtion NEGative) is substituted for the corresponding emoticons.

Hashtag: Users regularly utilize hashtags, which are unspaced words prefixed by the hash sign (#), to reference a current topic on Twitter. The words with the hash symbol have taken the place of all the hashtags. For instance, hello is used instead of #hello. Is the regular expression used to match hashtags #(S+).

Retweet: Retweets are tweets that have already been sent and are being shared by other users. Tweets with the characters RT (Reposting of a Tweet) are retweets. RT is taken out of the tweets because it isn't a critical component for text classification. Retweets are matched using the regular expression \brt\b. Following tweet level pre-processing, the following processing is done to each word in a tweet:
I Remove all punctuation from the word ['"?!,.():;].
ii) Reduce word repeats of two or more letters to two letters. Some people use numerous characters in their tweets to highlight key terms such as, I am sooooo happpppy. These tweets are managed by converting them to "I'm so happy" in this manner.
iii) Take away " and ". The more broad forms t-shirt and their's are used to handle terms like "t-shirt" and "theirs."
iv) Check the word for validity and accept it only if it is. A valid word is one that starts with an alphabet and ends with an alphabet, a number, or either a dot (.) or an underscore (_).
Replace negative references. Tweets feature a wide range of negative concepts. In general, negation is significant in defining the polarity of a tweet's sentiment. Here, "won't," "can't," and "n't" are being negated individually by becoming "will not," "cannot," and "not." Extend slang and abbreviations to their full word forms. Slang and acronyms are frequently used in tweets but are poorly formed words. For the purpose of sentiment

analysis, they must be expanded to their original entire words form.

Data labeling allows DL algorithms to gain a thorough understanding of real-world environments and conditions. A common starting point for data categorization is to gather opinions from people regarding an certain set of unlabeled data. The unlabeled and unstructured data domain is the focus of many data science issues. Clustering is a key technique for analysing unlabeled data. Understanding how to cluster is more crucial in this situation. Clustering can only be done on numerical values as it primarily calculates the similarity of each datapoint with respect to others by calculating their mathematical distance (Euclidean, Manhattan, Minkowski, etc.). Hence, one can either cluster the textual data points by converting them into a numerical dissimilarity matrix, or cluster them by understanding the semantics of the textual datapoints by vectorizing and clustering them by their word embeddings.

If a tweet has 4 positive, 2 neutral and, 2 negative words, then the sentiment of the tweet will be calculated as: Thus, the tweet would be marked as positive as it has more positive dominant words.

The Word2Vec and GloVe word embedding models were utilized in this study (Global Vector for Word representation). 25-dimensional word vectors were produced using the Word2Vec model. The CBOW (Continuous Bag of Words) model was utilized in the development of Word2Vec. In addition, words that only appeared four or more times are eliminated. The maximum skip distance between words was then adjusted to 5. The Word2Vec model is used to extract the concept of relatedness across words or products for applications such as semantic relatedness, synonym detection, concept classification, selectional preferences, and analogies. GloVe is a distributed word representation approach that is derived from Global Vectors. The algorithm used by the model to learn word vector representations is unsupervised learning. This is accomplished by translating words into a significant space where the distance between words is connected with their similarity measures. With its pre-trained word vectors, GloVe is used. The following equation is used to standardize each and every vector:

$$v_i' = \frac{v_i - v_{min}}{v_{max} - v_{min}} \quad (1)$$

Where v_i' is a 25-dimensional vector's normalized i-value, v_{min} is the vector's minimum value, and v_{max} is its highest value.

The word vectors of a tweet are synthesized to generate a singular vector before the sentence vectors are created. To maintain information in a phrase and long-distance dependency across sentences throughout the prediction process, a supplemental strategy in word embedding is to partition the word vectors of a sentence in regions. The punctuation marks on a sentence are used to divide content.

By identifying the words that occur opposite each phrase in the tweet, they can simultaneously determine its context. The sentiment polarities of each sentence are estimated by looking at the orientations of the words that are commonly seen together. This method differs from others in that it does not give words predetermined prior sentiment polarity. In order to capture the contextual semantics of words, it takes into account their co-occurrence patterns in various situations. The statement "You shall know a word by the company it maintains" serves as the main tenet of the concept of contextual semantics. Besides that, this suggests that words that co-occur in a given context have a specific relationship to each other, which, if captured, can provide insights into their sentiment orientations and significantly enhance sentiment analysis accuracy. Following the discovery of the co-occurring terms, the sentiment lexicon VADER is used to ascertain the overall sentiment polarities of all these co-occurring words.

The VADER (Valence Aware Dictionary and sEntiment Reasoner) Lexicon is used to determine the overall sentiment polarities of all co-occurring words after they have been found. Additionally, VADER does a fantastic job of managing slang, acronyms, and emojis. It not only expresses the polarities of the sentiment, such as positive or negative, but also its strength, or how powerful the sentiment actually is. It outputs four scores: positive (pos), negative (neg), neutral (neu), and compound, or overall score. Scores show how much of the text falls into the positive, negative, and neutral categories. An overall value resulting from all normalized language ratings is known as a composite score.

SentiCircle's main premise is that a word's orientation is dynamic and constantly changes depending on its context, rather than being static or fixed. To determine the target word's eventual polarity, SentiCircles of the target word are created while taking into consideration its co-occurring words (and their obtained polarities). That is, the SentiMedian of the SentiCircle is used to calculate the final sentiment polarity for each phrase, and then for each tweet that follows.

In order to train and test the LSTM model for tweet sentiment categorization, the embeeded data is separated into two parts, training and testing data. A form of RNN (Recurrent Neural Network) that can learn long-term dependent is the LSTM. RNNs (Recurrent Neural Networks) are a particular category of neural network models that are specialized to sequential data, like texts. These models (RNN and variations) have demonstrated their effectiveness in sentiment analysis tasks. The RNN linearly integrates the system's current state and the time step's input features in each time step. The outcome is then given a non-linearity. The RNN type called LSTM can learn complex units of long-term dependence connections. The LSTM determines which knowledge should be maintained and which new information should be forgotten at each time step. As additional baseline, the LSTM model is trained. The LSTM determines which knowledge should be maintained and which new information should be forgotten at each time step. Four discrete computations are carried out in each cell using the following gates: input (*it*), forget *(ft)*, candidate *(ct)*, and output *(ot)*. The following are the equations for these gates:

$$f_t = sig(Wf_{xt} + Uf_{ht} - 1 + b_f \quad (2)$$
$$i_t = sig(Wi_{xt} + Ui_{ht} - 1 + b_i \quad (3)$$
$$O_t = sig(Wo_{xt} + Uo_{ht} - 1 + b_o \quad (4)$$
$$c{\sim}t = \tanh(wc_{xt} + Uc_{ht} - 1 + b_c \quad (5)$$
$$c_t = (f_{to}ct - 1 + i_{to}c{\sim}t)(6)$$
$$h_t = O_{to} * \tanh(c_t) \quad (7)$$

In this example, tanh stands for the tangent activation functions, X stands for the input data, W and b stand for the weight and bias factors, respectively, C_t stands for the cell state, c ~ t stands for the candidate gate, and h_t stands for the output of the LSTM cell. The SentiScore of each tweet is aggregated to get its final emotion direction. The final outcome of the methodology is a five-class fine-grained segmentation of sentiment analysis into highly encouraging, highly negative, neutral, and highly positive categories.

4. RESULT ANALYSIS

In this approach, sentiment analysis based twitter tweets classification using embedded data with LSTM is implemented using python. The result analysis of presented approach is demonstrated here. Firstly, the twitter data is collected. The collected data is pre-processed to remove the unnecessary data and to transform into required format. The twitter data contains different symbols, emojis, emotion, special characteristics, the data embedding methods wordV2c and Glove is used for the vector representation of words. The LSTM is used to identify the sentiments in the tweet. The polarities of tweets are categorized using the Vader Sentiment polarity as negative, positive, neutral, very positive, and highly negative. The following criteria are used to evaluate this method's effectiveness:

True Positive (TP): the proportion of tweets that are both positive and appropriately categorized as positive.

True Negative (TN): the proportion of tweets that are both really negative and appropriately categorized as negative.

False Positive (FP): how many tweets are misclassified as positive when they are truly negative.

False Negative (FN): how many tweets are misclassified as negative when they are truly positive.

Accuracy: The ratio of correctly classified instances to total classified instances is defined as accuracy.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (8)$$

True Positive Rate: It counts the number of records that are accurately categorised as positive out of the total positive records. It is also known as the sensitivity or recall and is expressed as

$$TPR = \frac{TP}{TP + FN} \times 100 \quad (9)$$

Precision: Precision measures how many of the instances are predicted correctly as positive and is expressed as

$$Precision = \frac{TP}{TP + FP} \times 100 \quad (10)$$

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The performance of presented approach is compared with twitter sentiment analysis using deep learning method and is shown in Table 1.

Table 1: Performance Metrics Evaluation

Twitter sentiment analysis approaches	Precision (%)	True Positive Rate (TPR) (%)	Accuracy (%)
Twitter sentiment analysis using Deep Learning (DL) method	72.3	73.4	76.4
Sentiment analysis based twitter tweet classification using data embedded with LSTM technique	94.3	94.23	95.6

For Twitter tweet classification, the LSTM technique performs well in terms of precision, True Positive Rate, and Accuracy, however Twitter sentiment analysis using DL performs less. Figure 2 illustrates a performance comparison in terms of TPR and Precision.

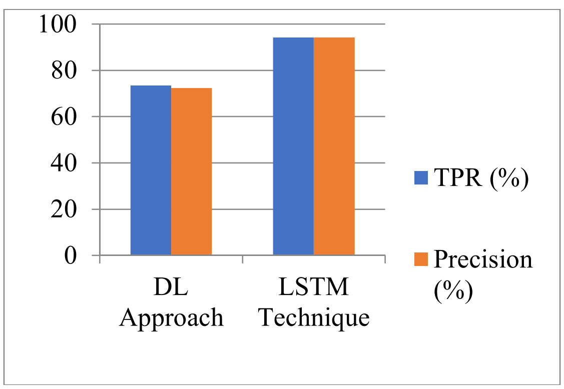

Fig. 2: Performance Comparison

Compared to DL (Deep Learning) approach, presented LSTM technique has high TPR (True Positive Rate) and precision. The Fig. 3 shows the sentiment polarities comparison of different sentiment polarities such as negative, positive, neutral, highly positive and highly negative. The x-axis represents different categories of tweets whereas y-axis represents the tweets percentage.

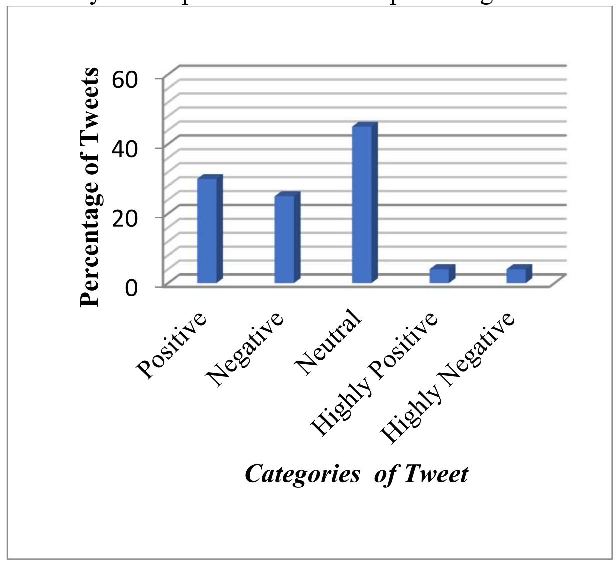

Fig. 3: Sentiment Polarities comparison

From the Fig. 3 it is clear that, in most of the tweets, the neutral polarity is high. Highly negative and highly positive tweets are less compared to other polarities. The Fig. 4 shows the accuracy of presented LSTM and DL approach for twitter sentiment analysis.

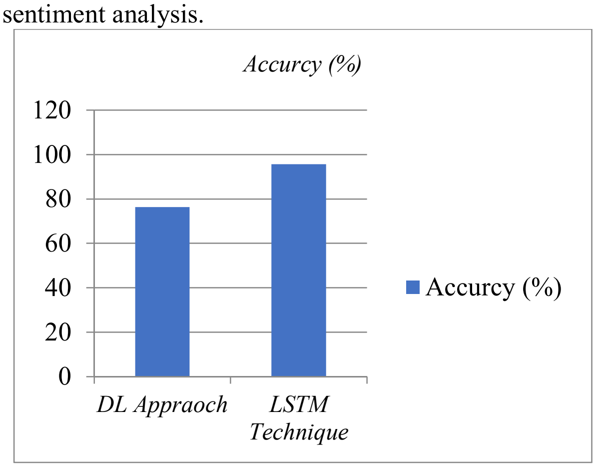

Fig. 4: Accuracy Comparative Graph

The LSTM technique has achieved high accuracy for twitter tweets classification whereas the DL approach has less accuracy. Hence the sentiment analysis based twitter tweets classification using data embedded with LSTM technique has effectively classified the different tweet polarities like positive, negative, neutral, highly positive and highly negative from the tweets collected in real time. As a result this approach provides several benefits like find out the brand perception; Builds stronger customer relationships; Offer better

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customer service; Identifies key emotional triggers; Discover new marketing strategies; Boost profits; Manage crisis better.

5 . CONCLUSION

In this work, sentiment analysis based twitter tweets classification using data embedded with LSTM technique is presented. Firstly, the real time tweets data is collected from twitter. Data labelling is done to lable the tweets as positive and negative. Data pre-processing is performed to remove the unnecessary data and to clean the data since Tweets data contains different characters, hashtags, special characters. Data embedding techniques like Word2Vec and Glove techniques are used to represent the twitter data into vector representation. The LSTM technique is used to identify the sentiments. The VADER sentiment polarities are used to determine different polarities in tweets. Finally using the sentiscore, the tweets are classified as positive, negative, neutral, highly negative and highly positive. The performance of presented technique is evaluated in terms of accuracy, precision and TPR. To evaluate the effectiveness of presented approach it is compared with Deep learning approach. Compared to DL approach, the LSTM technique has better TPR, Precision and Accuracy. This approach is an effective one for classifying the various real time twitter texts.

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