An Efficient Approach for Sentiment Analysis using Convolutional Neural Network

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Abstract: Sentiment analysis is a substantial area of research nowadays. Many researchers have proved the subject in recent years. The reason behind that is the rapidly growing opinionated data on social media. With the aim of surmounting this obstacle, we introduce an efficient approach for sentiment analysis that ensemble the advantages of two deep learning models. Sentiment mining is the process of extracting opinion, feelings, emotions and attitude towards a specific task. Here, we have collected the IMDB movie review dataset as well as used two kind of deep learning classifiers to analyze the experimental result. Hence, the contemplated models are Long Short Term Memory and Convolutional Neural Network. The efficiency of the proposed model is compared with other traditional approaches in experimental work and outcome of the result shows that the ensemble approach can effectively improve the accuracy to predict the sentiments.

1 INTRODUCTION

Natural Language Processing(NLP) is a discipline in computer science that deals with the communication between machines and humans in natural language. NLP is dealt with enabling machines to understand and develop the human language. There are numerous application of NLP such as text categorization, sentence classification, Named Entity Recognition, speech recognition, Language detection and summarization, character recognition, structure prediction, decision making, computer vision, and others. It is one of the substantial applications of Natural Language Processing.

Sentiment classification has become the most effective research area in NLP due to an increase in public interest in movies, outlooks, and elections. It aims to identify opinions, emotions, and attitudes towards specific tasks like movies, events, elections and many more. The rich data sources are used to perform analysis, likewise social media sites, blogging sites, RSS news feed etc. To perform text classification, it includes different processes likewise feature extraction, emotion detection, and attitude extraction. In the real world, there exist various application areas likewise in the medical field, box office, commercial sites, politics, and business intelligence.

If we look further in the analysis process, there are used some notations such as subjective, objective, polarity and sentiment level. When the sentence holds subjective orientation in a given piece of text then it is known as subjective. For example "Newton is an awesome movie." An objective can be defined as the sentence holds objective orientation. For example "Amit Masurkar is the director of Newton movie". The other notation is polarity detection and it can be split up into three parts likewise positive, negative and neutral. Sentences show different levels of polarity such as I love my friends, I hate liars,I usually go outside every weekend. The first sentence contains positive polarity, the second sentence contains negative polarity and the third one contains neutral polarity respectively.

2 RELATED WORK

In order to do the analysis of sentiments, numerous researchers have made their efforts to ensemble deep learning andmachine learning classifiers to achieve outstanding result in ongoing years. The related

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work briefly elaborates on the numerous researches, associated to text classification of social media contents about people's sentiments, feelings, reviews towards various subjects like movies and products using NLP techniques.

The authors have proposed an efficient deep learning classifier for sentiment classification which calculates the accuracy of 82.53% on Bengali text. In order to evaluate the performance, they used two deep neural network models such as deep RNN with BiLSTM (Sharfuddin AA, 2018). Deep learningtechniques achieved significant results in textanalysis. (Chen S, 2018) has been proposed an innovative method for target-based sentiment analysis which reduces the training time of the proposed model through regional LSTM. Deep learning models are frequently used in NLP applications. An efficient approach has been proposed for the multi-domain system that is based on word embedding. The tool named NeuroSent gives an accuracy of 85.15% by using the Amazon web site dataset for multi-domain (Dragoni M, 2017). Some of the deep learning models are based on sentence classification in Natural Language Processing and some of them are based on traditional models like SVM, RNN, LSTM and much more. In this literature survey, we basically study the ensemble approaches to improve the performance. Some authors proposed an ensemble method for text classification by using Vietnamese text. In this technique, they have merged the traditional modelswith deep learning models and achieved the remarkable result that is 89.19% (Nguyen HQ, 2018). Some authors have done their research study in artificial intelligence on deep learning models. The review basically focuses on text classification by using different datasets (Alwehaibi A). A novel approach has been proposed by authors that are based on an ensemble of two models and achieves the accuracy 89%. They have used the IMDB movie review datasetfor the analysis process [6]. The ensemble approach gives outstanding results over traditional models in text analysis. We noticed that the ensemble approaches performed much better than traditional models. Some authors have proposed a machinelearning-based approach for improving the performance of sentiment analysis. They have used LSTM, Naïve Bayes and SVM for analysis process (Day MY, 2017). Some authors have gained remarkable results in the field of Natural Language Processing by using deep learning techniques for text classification (Hassan A, 2017). In order to do classification, the authors have used Tibetan microblogs and achieved the result up to the mark (Sun B, 2018).

The deep learning-based models improve the result in the field of NLP over the years. The authors have proposed a model named SentiWordNet and achieved better results. The model used word2Vec to perform analysis (Alshari EM, 2018). A novel approach ECNN has proposed that is used to identify opinion, polarity, and emotions in microblogs (Yang G, 2019). Numerous researchers have proposed a model related to sentiment classification. They have used word embedding methods of learning at the word level and sentence level (Zhang Z, 2015). In this field of research, we can achieve better results by using deep learning-based approaches. The authors have proposed an ensemble approach that is the result of two machine learning models CNN, SVM for text sentiment analysis (Cai J, 2018). Many researchers have proposed an efficient method to perform classification processes on the IMDB review dataset and they found that RNN performs effectively in terms of words semantic and they achieved an accuracy of 89.8% (Zharmagambetov AS, 2015). In order to perform analysis, there are different parameters used such as feature extraction, opinion mining, applying different kinds of machine learning algorithms. An approach has been proposed that is based on a machine learning and Lexicon based features to perform sentiment analysis on the movie review dataset (Bandana R. 2018). Word embedding is a technique that is used to convert the words into vectors. The researchers have been using the word embedding method for sentiment analysis. An efficient approach has been proposed for sentiment analysis by using word embedding (Deho BO, 2018).

The comparative study is done by researchers on different tools and techniques of machine learning approaches of Natural Language Processing. The paper presents the various feature selection methods and machine learning techniques (Mejova Y, 2009). A joint framework has been proposed for sentence classification based on CNN and RNN. It gives the accuracy of 93.3%, 48.8%,89.2% on the movie review dataset, fine-grained and binary accuracy respectively (Hassan A, 2018). The authors have proposed a deep learning approach for the classification process. (Patel Alpna, 2019) have achieved an accuracy of 87.42% by using RNN. The researchers have presented a novel approach to extract features and textual modalities and to improve the performance, they have used a deep CNN approach for the classification process (Poria

S., 2017). (Ruangkanokmas, 2017) have been proposed a model named Deep Belief Network. They have used a semi-supervised learning method called Deep Belief Network. The authors have proposed a method for users' interests classification based on CNN and Word2Vec. The proposed framework is based on deep learning and they used CBOW as a feature extraction algorithm and SVM for classification that gives the accuracy 96% on the IMDB movie review dataset (Om, A. H., 2017). (Changliang Li, 2018) builds the Chinese Sentiment Treebank over social data and further introduces an approach named Recursive Neural deep model for the analysis process. The authors have been using word vectorization to extract corpus features and PCA to reduce dimension (Li, C., 2014). (Kumar Ravi, 2018) performed sentiment analysis on article citation sentences and they have been proposed an ensemble method for deep learning. The authors have been performing sentiment analysis by using word embedding techniques like word2vec and Glove as a pre-trained vector (Henry, S., 2017).

The author DoaMohey El-Din Mohamed Hussein has done the comperative study on sentiment mining challenges (Hussein, 2018). (Feilong Tang, 2019) have been proposed a model named JABST stands for joint aspect-based sentiment topic for multi-grained aspect by using supervised learning method to process the model. The authors have been presented as an attention mechanism for target-level and context-level attention. The presented mechanism is more effective for sentiment feature (Yang, C., 2019). (AbinashTripathy, 2015) focuses on machine learning techniques. They obtained the result by using Naïve Bayes and SVM and show the comparison on the movie review dataset. The authors have shown the comparison between two classifiers named Deep Recurrent Neural Network and SVM. They concluded that the Support Vector Machine performs much better than Deep Recurrent Neural Network (Al-Smadi, M., 2018). (Rodrigo Moraes*et.*, 2013) have been presented with an empirical comparison between ANN and SVM on the movie review dataset and they found ANN performs better than SVM. The authors have presented an ensemble deep learning method for sentiment analysis by using the IMDB movie review dataset (Araque, O.m, 2017).

(Abinash, 2016) presented a novel technique for sentiment mining. They used an ensemble of classifiers named Naïve Bayes, SVM and Stochastic Gradient Descent and achieved an accuracy of 83.33% on the IMDB movie review dataset. (Giatsoglou Maria, 2017) have been presented with an approach named RAE and achieved an accuracy of 83.99%. The authors have been performed better by using micro-blogs text (Zhang, S., 2018). (CagatayCatal, 2017) have proposed a model for analysis. The model has achieved the accuracy of 86.13%. The authors have proposed a model named ML-KNN for classification. They used the unsupervised learning method (Zhang, M. L., 2007). The authors have presented a review on research topics, venues and top-cited papers (Mäntylä, M. V, 2018). The authors have been presented with a boosted ensemble-based classifier for sentiment analysis (Athar A, 2017). Anuj Sharma *et. al.* have been presented with aboosted approach based on SVM (Sharma A, 2013; Dumoulin J, 2015). The authors have been using a hierarchical approach for analysis (Sharma A, 2013). (Sharma A, 2012) gave the literature survey on the ensemble of the classifier for sentiment mining. The authors have been using a deep neural network for sentiment prediction (Piao G, 2018). (Wan X., 2008) applied ensemble techniques for unsupervised Chinese sentimentanalysis (Piao G, 2018).

3 PROPOSED APPROACH

This section presents the detailed overview of the proposed model to classify sentiments in movie domain. The proposed approach uses two classifier of deep learning i.e Long Short Term Memory and Convolutional Neural Network. It uses word embeddings as input and takes them to LSTM for feature extraction and further output is given to CNN and followed by classification layer. The following step is followed by a proposed approach:

- Word Embedding method is used to convert the word into featured vectors in the given text.
- The hybrid model takes the advantages of two deep learning approaches such as LSTM and CNN for feature extraction.
- The classification layer uses the Softmax activation function to compute the predictive probability.

3.1 Long Short Term Memory Architecture

Long Short Term Memory is a deep neural network model that is used for sequential information and proposed by (SeppHochreiter, 1998). LSTM is RNN architecture that REMEMBERS values over arbitrary intervals and used to resolve a problem of vanishing gradient problem (Schuster M, 1997; Hochreiter S., 1998; Zhou C, 2015). LSTM enables RNN's to remember their inputs over a long period of time. It uses input gate, forget gate and output gate as gates. The input gate is used for new input in, forget gate for whether information delete or not and the output gate for output at the current time step (Liu P, 2016; Tang D, 2015). The LSTM Architecture is depicted in figure 3.

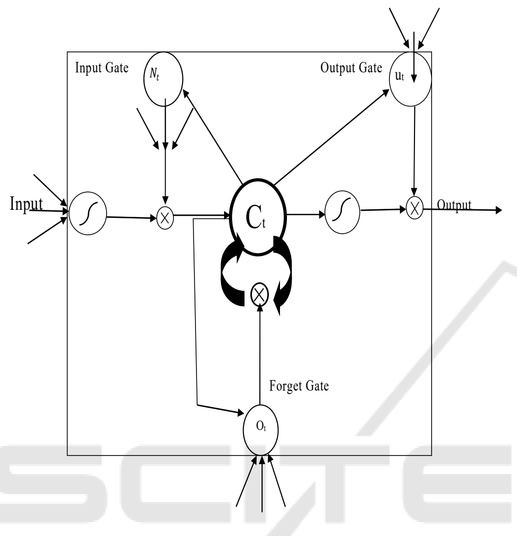

Figure 3.1: The LSTM gate architecture

The sigmoid function gives the output value between 0 or 1. The equation is given below:

Input gate equation

$$I_g = \sigma(w_n[h_{g-1,}x_g] + b_n \tag{3.1}$$

Forget gate equation

$$F_g = \sigma(w_o[h_{g-1,}x_g] + b_o \tag{3.2}$$

Output gate equation

$$O_g = \sigma\left(w_u[h_{g-1,}x_g] + b_u\right) \tag{3.3}$$

where I_g represents the input gate, F_g as forget gate, O_g as output gate, σ denotes the sigmoid function, w_x shows the weight for the respective gate (x) neurons, $h_{(g-1)}$ represents the output of previous LSTM block, x_g shows input of current timestamp and b_x shows the biases for relative gates. The equations are given as follows:

Cell state equation

$$\acute{c}_t = tanh(w_c[h_{t-1,}x_t] + b_c) \tag{3.4}$$

Candidate cell equation

$$c_t = f_t * c_{t-1,} + i_t * \acute{c}_t \tag{3.5}$$

Final output equation

$$h_t = o_t * tanh(c_t) \tag{3.6}$$

where ct denotes the cell state at t timestamp and ćt shows candidate for cell state at t timestamp. we evaluate the above equation that our cell state knows that what it needs to forget from previous state (ft*ct-1) at any timestamp and what it should include from current timestamp (it* ćt) and * represents the element-wise multiplication. Next, we refine the cell state and pass it to the activation function (Nowak J, 2017; Nabil M, 2016).

3.2 Convolutional Neural Network Architecture

Convolutional Neural Network was initially developed in the neural network image processing community. CNN involves basically two operations for text classification such as convolution and pooling as feature extractors (Lai S, 2015). CNN uses two kinds of pooling as feature extractors such as max-pooling and average-pooling. The max-pooling elects a maximum number of values in the input feature map and the other selects the average number of values in the region (Lee JY, 2016).

Convolutional Neural Network is also applied to the text in Natural Language Processing. When we use CNN for text instead of images, then we use the 1-D array to represent context (Yin W, 2017). Mostly in Natural Language Processing (Nasukawa T, 2003) task, CNN is used in sentiment analysis which means classifying a sentence into a set of predetermined categories. In order to perform text classification, each sentence is known as matrix. Every row of the matrix shows the one token, typically a word. We can say that each row is vector and impersonate a word (Guggilla C, 2016).

In the NLP task (Kao A, 2007), we have used filters over full rows of matrices. The following model is as follows:

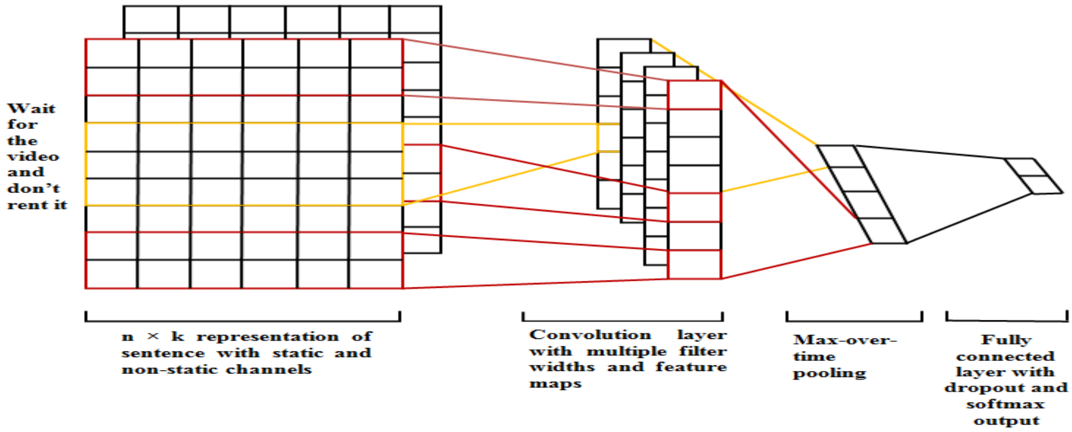

Figure 3.2: Convolutional Neural Network Model Structure

If we analyze the above model, then we see that the first layer embed words into low dimensional vector after that next layer performs convolutions over the embedded word vectors using multiple filter sizes and classify the result using a softmax layer (Conneau A, 2016). We have used CNN for text analysis for sentiment classification on the IMDB movie review dataset (www.kaggle.com).

3.3 The Embedding Layer

This layer of network changes the words into real-valued featured vectors. Our model takes input in the form of vectors. In order to convert words into real-valued featured vectors, we have used the word embedding method. Word embedding is the process of representing the word or phrase into a vector. The word is stored in vocabulary and arranged sequentially. We have used distributed representation to overcome the dimensionality problem.

3.4 The Proposed Approach

In this subsection, we have discussed the detailed framework architecture of our proposed approach. The proposed approach ensemble the advantages of two deep learning classifiersi.e LSTM and CNN. Previously, we provideda detailed architectural explanation of LSTM and CNN. If we look upon RNN, the Long Short Term Memory approach performs efficiently related to feature extraction. In this approach, the convolutional layer uses Max-pooling. The ensemble approach uses the embedding layer to take the input in the form of words and pass it to the multi-layer LSTM model. The multilayer LSTM generates the output and it is further passed to the convolutional layer as an input for further process. After the output of the convolutional layer passed to the classification layer for the classification process. The convolutional layer extracts the features of text sequences.

LSTM model gives the output; L= $[L_1, L_2, L_3, ..., L_t]^T$, $L_t$denotes the t^{th} words of the n-dimensional vector in a given sequence. The number of LSTM hidden layers and the vector length both are equal. C= $[C_0, C_1, C_2, ..., C_{n-1}]$ will produce one value at t time step as follow:

$$\mathbf{U_{Ct} = ReLU\ [(\textstyle\sum_{i=0}^{n-1} O_{t+1}{}^{T} C_i) + b]} \quad (3.7)$$

where, b denotes the bias value and combination of b and C are used RELU activation function(C(y) = max (U, y)). It shows the single convolutional filter to extract the value of features from a given text sequence. The proposed approachis used multiple convolutional filters to extract variousfeatures. Next, the max-pooling layer formed and passed to the fully connected layer. The classification layer uses the Softmax activation function to calculate the predictive probability for all categories. The following equation shows the probability y as category w:

$$\mathbf{P(x^{(i)} = w|y^{(i)}; \theta)} = \frac{e^{\theta_j^T y(i)}}{\sum_{k=1}^{K} e^{\theta_j^T y(i)}} \quad (3.8)$$

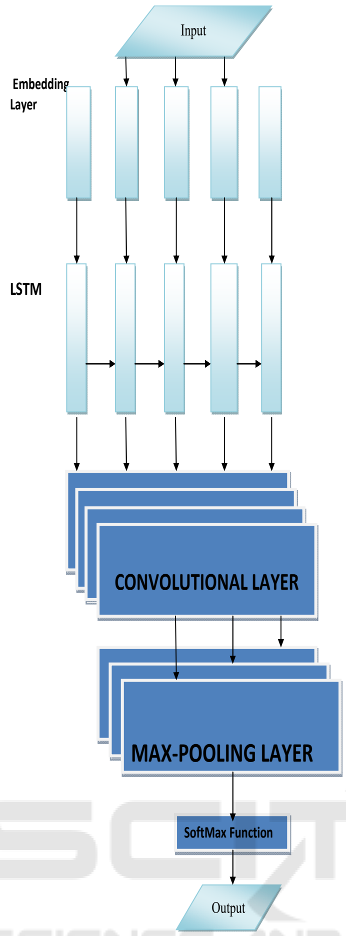

Figure 3.3: The Framework of the Proposed Approach

4 RESULT AND DISCUSSION

This section briefly discusses the experimental setup and measures the result of the approach. The performance was evaluated by using different parameters. The following subsection contains detailed information about datasets, experimental setup, confusion matrix, etc. These are as follows:

4.1 Dataset Description

In order to evaluate the performance, we have used the IMDB dataset. It includes 25000numbers of data on movie reviews from the Kagglewebsite that contain binary values named positive and negative sentiment. This paper uses the IMDB movie review dataset for the purpose of experimental work, the dataset contains 25000 numbers of data in which a 75% number of data for the training set and 25% number of data for the validation set. After the split the dataset, further we perform dataset preprocessing tasks to clean the raw data and break the sentences into words and words into text. The detailed process is given in the introduction section.

4.2 Environmental Setup and Param Setting

Anaconda is a package provider for machine learning models by using python language. Tensorflow is the framework that provides the environment for machine learning models. We have used python version 3.6.5, jupyter notebook and Keras for implementing deep neural network models. Keras is the higher-level API that uses TensorFlow in backend and it is used for sequential modeling. In this experiment work, we used categorical cross-entropy for loss, Adam optimizer with learning rate 0.001, the batch size is 32 and the hidden layer of LSTM is 128 with dropout 0.2.

4.3 Performance Measure

If we look to the performance of the proposed model, a confusion matrix has been used that contains some parameters such as *tp* as true positive, *tn* as true negative, *fp* as false positive, and *fn* as false negative on test data. The confusion matrix is given in Table I as follows:
It is used to calculate the accuracy of the proposed approach by using the following formula:

$$\textbf{Accuracy}=\frac{tp+tn}{tp+tn+fp+fn} \text{X } 100\%$$

The parameter accuracy is used to validate the proposed hybrid model by using the test set and validate set. The Table II depicted the comparative result of the proposed approach with deep learning approaches:

Table 1: Confusion Matrix

	Label 1 (Predicted)	Label 2 (Predicted)
el 1 (Actual)	*tn*	*fp*
el 2 (Actual)	*Fn*	*tp*

Table 2: Accuracy Comparison of Ensemble Approach with Deep Neural Network Model for Sentiment Analysis

	Deep Learning Models	Time (per second)	Test Accuracy	Valid Accuracy
1.	Bidirectional LSTM	2119	88%	84.85%
2.	LSTM	1164	89%	85%
3.	CNN (max- pooling)	575	97%	85.52%
4.	CNN+GRU	551	95%	85.61%
5.	Bidirectional GRU	2676	89%	85.64%
6.	**DeLC model**	**1026**	**91%**	**85.78%**

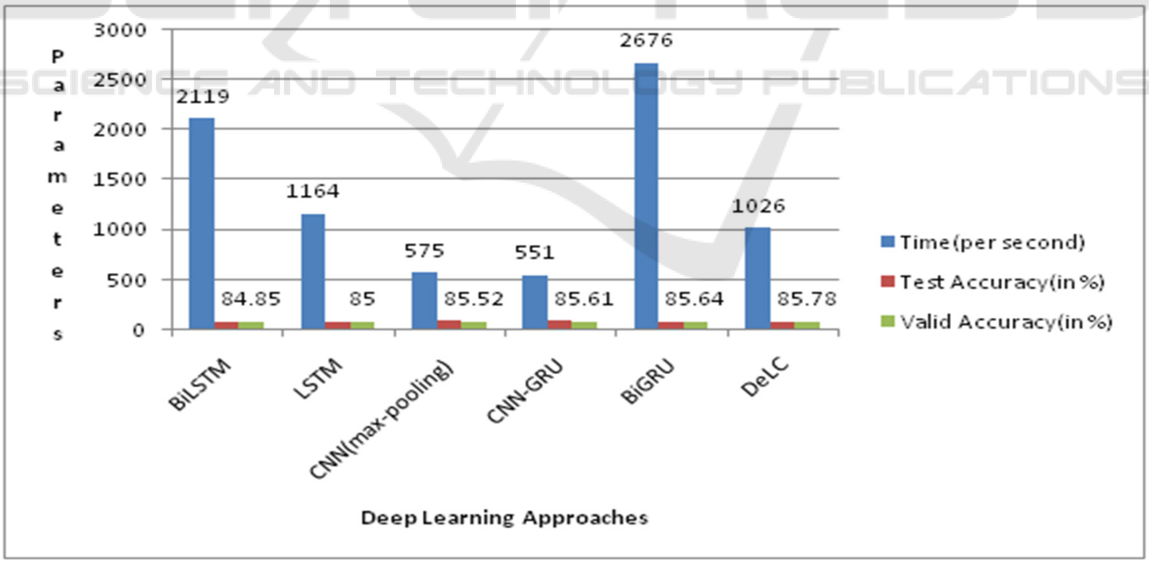

Figure 3.4: Comparative study of proposed approach over Traditional Approaches

Here, we compare the outcome of proposed approach over traditional approaches. The experimental work give the result analysis as follows, Bidirectional LSTM gives the accuracy 84.85%, LSTM 85%, CNN 85.52%, CNN-GRU 85.61%, Bidirectional GRU 85.64% and DeLC hybrid model gives the valid accuracy 85.78%. We can see that the proposed approach gives the outstanding result over other deep learning approaches. The figure 3.4 shows the comparative result of the proposed approach with deep learning models including some parameters such as time (per second), test accuracy and valid accuracy.

The figure 3.4 shows the comparison of existing approaches with the proposed approach in terms of time, test accuracy and valid accuracy. If we look forward to the analysis process, we found that the proposed approach may perform better in relation to other deep learning approaches. The experimental result shows that the proposed approach performs effectively with an accuracy of 85.78%.

5 CONCLUSION

Sentiment classification is the method of extracting a user'sview as positive or negative for a specific task. We have introduced an efficient approach for sentiment analysis that ensemble the advantages of two deep learning models name as Long Short Term Memory and Convolutional Neural Network. LSTM overcomes the vanishing gradient problem and preserves historical information of long term text dependencies. Further, CNN extracts the feature of context. In this paper, the proposed ensemble approach efficiently improves the accuracy of sentiment classification. The proposed ensemble approach gives an accuracy of 85.78% on IMDB movie review data. It is found that the proposed approach performs better than other deep learning approaches.

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