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Convolutional Neural Network based sentiment analysis with TF-IDF based vectorization

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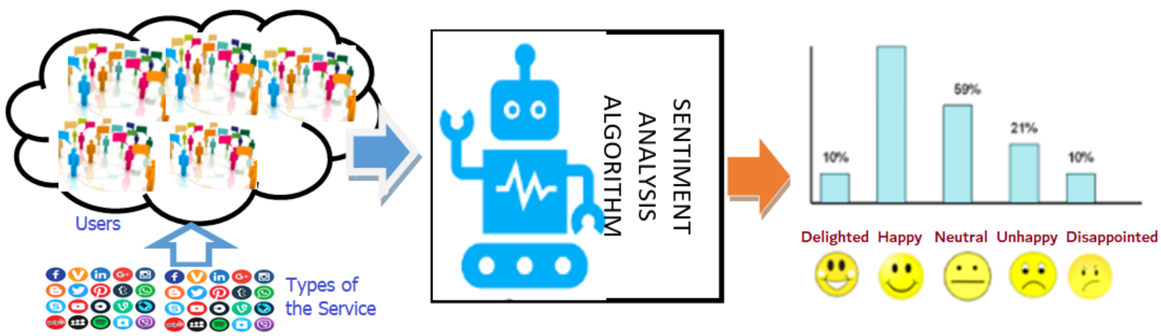
ABSTRACT



Recent years have seen an increase in interest in sentiment analysis (SA), which is the process of determining if a textual item (such as a blog article or customer review) communicates a favorable or negative opinion about a certain entity (such as a business, people, or government) in general. It plays a crucial part in natural language processing (NLP). The growth of user-generated material in recent years, such as traveler reviews, has resulted in a significant volume of unstructured data that is challenging to extract usable information from. Predicting the precise sentiment polarity of the customer reviews, user ratings, recommendations, etc. is still a difficult problem, particularly for fine-grained sentiment categorization, because of the variations in the length of the sequence, text order, and complex logic. This research first proposes sentiment analysis using deep learning, a unique approach compared with other existing techniques which make the input data sample a constant sizing and enhances the percentage of sentiment data in each review. This research present CNN-TDIDF family models, which combine CNN and TF-IDF in parallel and are based on deep learning, and are inspired by the most current research on neural networks. Experiments on several difficult datasets show that the suggested strategy performs better than many standard approaches. This model has been shown to operate better than conventional machine learning methods and reach 87 percent accuracy rate. Comparing this work to past efforts, study also able to attain a very high accuracy rate.

Keywords: Convolution Neural Network, Deep Learning, Opinion Mining, Polarity, Sentiment Analysis.

INTRODUCTION

All types of human interaction include emotions. They often influence how one feels about a situation, subject, activity, etc. Through a variety of channels, including remarks, comments, and message boards, which together may include textual, videos, polling, and other content,[1] study gather feedback and opinions on a wide range of items, whether online or off.[2] Every sort of feedback contains some form of emotion, such as whether the overall experience was favorable, bad, or neutral. Understanding the underlying mood behind all of these views is the key issue for a computer. Additionally, with the fast advancement of information technology, the Internet has taken on a crucial role in people's lives.[2,3] On many platforms, such as Web forums, blogs, social networking sites, etc., individuals primarily exchange their thoughts regarding various entities, such as goods and services. These platforms include useful data on a range of topics, including economic, political, and social uses.[4] It is challenging to manually process this much data for analysis.

Sentiment analysis is the extracting emotions from data, including text, photos, and other types of data, and classifying that data depending on what the users are being conveyed[5] as shown in Figure 1. This may be used to discover hackers and troll accounts

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on social networks as well as classify user evaluations and public opinion on goods, services, and even specific individuals into positive and negative categories.[6] There are various aspects to take into account to extract the overall emotion, including those that go beyond basic words, even if it may sometimes be relatively simple (for instance, if the text comprises a few specific terms.

SA, often called opinion mining, is a technique used in NLP to determine the emotional undertone of a document. This is a common method used by businesses to identify and group ideas regarding a certain product, service, or concept. Text is mined for sentiment and subjective information using data mining, ML, and AI.[7] Technologies for sentiment analysis assist businesses in extracting information from unstructured, disorganized language found in online sources including emails, blogs, chatbots, websites, media, and reviews. By using rule-based, automated, or hybrid approaches, algorithms replace human data processing. While automated systems use machine learning methods to learn from data, rule-based systems use predefined,[8] and lexicon-based rules[9] to do sentiment analysis. Both methods are used in a hybrid sentiment analysis.[10] Opinion mining may extract the topic, opinion holder, and polarity (or the degree of positivity and negative) from the text in addition to recognizing emotion. In addition, sentiment analysis may be used in a variety of contexts, including text, sentence, phrase, and sub-sentence levels.[11]

Deep learning models have largely taken on the role of many traditional methods for resolving different computer vision and NLP problems as a result of deep learning's increasing significantly in recent years and the abundance of labeled data.[12] End-to-end modeling is utilized in these methods to simultaneously train the classification model and carry out classification,[13] as opposed to manually collecting features from textual data and images and sending them to a classifier. Figure 1 shows the systematic basic workflow of sentiment analysis using the deep learning method. With regards to sentiment analysis, information retrieval, machine translation, word embedding, and named entity recognition in natural language processing (NLP)[14,15] as well as image classification, object recognition, segmentation techniques, and image generation, deep learning-based designs have already been capable of achieving state-of-the-art achievement. As a result, CNN has been used in this study to conduct SA on text. CNNs are used since they recently outperformed image classification and NLP in terms of performance.[16] In contrast to other deep learning techniques like RNN, just need to artificially label the whole phrase, exactly like in the case of CNN. With convolution, a portion of relevant data can be retrieved together as the features, and CNN canconsider the connection between these features.[17] CNN can extract a region of features from global information. Because of this, text data can be used to do the same technique to create input features for a network that could be developed in an equally effective manner for sentiment analysis. Numerous CNN models were developed for experimenting by adjusting parameters like the number of convolutional layers, the number of filters and the size of the filters to find and calculate the performance of the framework. Analysis of the suggested CNN model's performance in comparison to other ML methods has also been done.[18]

Social media platforms like Instagram, Youtube, Facebook, and many more have grown rapidly during the last ten years. Companies and businesses have discovered that these platforms may be a priceless informational resource that enables them to communicate with and understand their consumers better. Monitoring a user's satisfaction level with a brand may be exceedingly difficult owing to the vast volume of customers, postings, remarks, emails, and other types of engagement. As an example, Twitter, Among the popular application sites today, has over 350 million active users who send out 500 million tweets daily. Deep Learning and other Machine Learning (ML) methods, however, may provide an automated way to assist in processing and extracting valuable data from these substantial volumes of information. For determining the polarity of the content, this study provides a deep learning-based sentiment analysis approach and integrates it with embedding and TF -IDF.

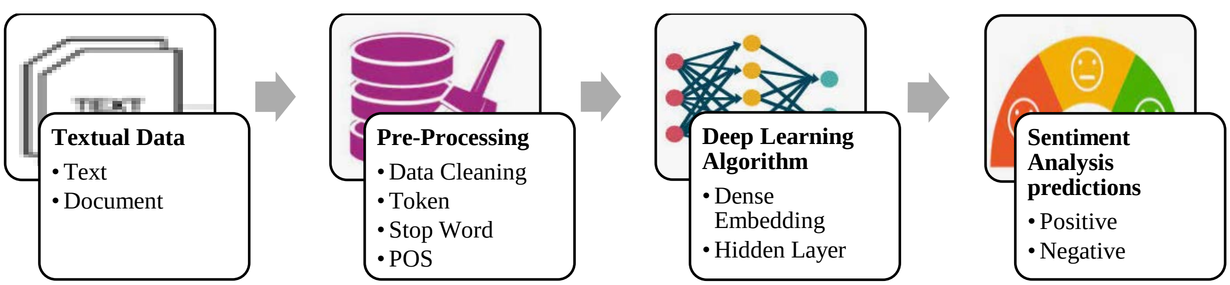

Figure 1. Sentiment Analysis Basic Workflow

LITERATURE REVIEW

Rodrigues et al.[19] focused on the identification of live Twitter spam messages and SA of both saved and live Twitter posts. Two distinct databases, including one SA and the other for spam identification, were employed in the suggested technique. For the classifying of Twitter spam, the multivariate regression naive Bayes classifier scored a validation accuracy of 98.74 percent, while the LSTM-DL model earned a classification performance of 97.78 percent. The classifying procedure proved that it is possible to accurately predict whether Twitter is spam or not using the features extracted from tweets. According to the classification outcomes, it is possible to reliably estimate the sentiment value of tweets using the characteristics extracted from them. For the Twitter sentiment classification, the SVM classifier had an accuracy of classification of 70.50 percent while the Long short -term memory classifier had an accuracy result of 73.81 percent.

Sitaula et al.[20] examined the emotion of Nepalese citizens using the categorization of tweets gathered from the social networking site Twitter. They initially suggest using three alternative feature extraction techniques for this. To implement the suggested features, three alternative CNN are suggested. To reach the final findings, next lastly assemble these 3 Convolutional models utilizing an ensemble Network, which operates in an end-to-end way. The research findings on this dataset demonstrate that the feature extraction techniques suggested have the discriminating qualities needed for sentiment categorization. This techniques significantly enhance classifier accuracy by (68.7%), which is an improvement of 9.2% percent over the worst method (59.5%) and a 5.8% boost over the foremost method (62.9 percent). With the same size range and a 95% F-1 score, there has been a considerable gain in classification accuracy

Hanane et al.[21] proposed a model by utilizing Forward-Backward encapsulating context data from Arabic features sequencing, an effective Bidirectional LSTM Network (BiLSTM). The findings on 6 benchmark SA databases show that the proposed framework outperforms both the industry-standard classical ML approaches and the most recent DL models. The system beats state-of-the-art techniques and also accomplishes various accuracy of 0.7205, 0.918, and 0.926 on this dataset.

Khan et al.[22] used the LSTM+CNN architecture together with conventional ML classifiers to analyze the quality of different word embeddings for Roman Urdu and English languages. The feature maps produced by CNN and LSTM are input to various ML classifiers to produce a complete result. This idea is supported by several word embedding systems. The suggested techniques perform very well in Roman Urdu and English text SA, according to extensive testing on 4 corpora, with accuracy values of 90.4%, 84.1 %, 74.0 %, and 74.8 % against different datasets, correspondingly. The findings indicate that although BERT word embedding, 2 layering LSTM, and Support Vector Machine as a classification function are better alternatives, the SVM classification is a more advantageous alternative for Roman Urdu SA. On applicable corpora, the proposed model beats the currently popular advanced versions, providing accuracy by approximately 5%.

Masood et al.[23] offered an Urdu-language application of SA.[23] A small-scale handcrafted lexicon comprising 830 Urdu stemmed words is first presented for processing and separating. Furthermore, for Urdu SA, a DL-based LSTM model is employed. The usage of LSTM, which efficiently collects sequencing information to assess attitudes, produces experimental results with a high accuracy rate of 86.03 percent and 0.89 F1 Score compared to traditional supervised ML algorithms.

Aslam et al.[24] performed sentiment analysis using tweets on cryptocurrencies that are often used to forecast market values for cryptocurrencies. LSTM and GRU are two frameworks of RNN that are combined in the DL ensemble model LSTM-GRU to increase the effectiveness of the analysis. The results indicate that using BoW features improves based on machine learning models. The suggested LSTM-GRU ensembles surpass both ML and cutting-edge models, with accuracy ratings of 99.0 % for SA and 92.0 % for emotion prediction.

Qureshi et al.[25] offered a classification scheme for the comments' polarities in Roman A fresh database of 24000 comments of Roman Urdu literature is developed for this study. 9 ML techniques are strived: Naive Bayes, SVM, Logistic Regression, KNN, ANN, Convolutional NN, Recurrent NN, ID3, and Gradient-Boost Tree. Depending on test and cross-validation accuracy rates of 0.9225 and 0.9147 correspondingly, logistic regression surpassed the competition.

Maity et al.[26] provided a variety of composite kernel functions that can be combined with SVM to create a model for subject SA of Tweets in Indian languages. Every combined kernel function is created by weighting the total of several single kernel functions that they have established. It uses multiple cutting-edge DL classifiers for subject sentiment classification in combination with the suggested approach. The suggested composite kernels SVM algorithm obtains the greatest accuracy score of 74 percent and the greatest percent F-score of 0.73 for datasets in the Indian language. The average accuracy and F-score for the DL approach, however, are 70 % and 71.31 percent, accordingly. The suggested technique outperforms the DL-based approach in the US airline Twitter dataset, with 83 percent accuracy and an F-score of 82% on averages.

Ishaq[27] offered a useful technique for sentiment analysis that makes use of CNN and GA. Aspect-based SA defines the link between a document's opinion targets and the polarization values that belong to them. It is quite difficult to identify characteristics and determine their distinct polarities since they are frequently implicit. Heuristic procedures are more accurate than frequency- and lexicon-based methods, but they take longer because of the many ways characteristics may be combined. The approach put out in this paper integrates 3 phases: Semantics mining (a), Word embedding corpus transformations (b), and CNN execution (c) for SA. Genetic algorithms are used to fine-tune CNN's hyperparameters. The suggested approach outperformed state-of-the-art procedures, according to experimental findings, with an average accuracy of 95.5 percent, precision rates of 94.3 percent, recall rates of 91.1 percent, and f-measure rates of 96.0 percent.

Ouyang et al.[28] provided an architecture termed Word2vec + CNN. To begin with, they create word vector forms using Google's word2vec algorithm, which will serve as the CNN's inputs. To get the word vectors of a word and express the distance between words, use word2vec. As a result, CNN's variables will be initialized at a favorable point, thereby enhancing the efficiency of the nets in this scenario. Second, create a CNN architecture that is appropriate for the SA job. Study approach to test on a collection of film review extracts, which is a publicly available dataset. It has five labels: negative, slightly negative, positive, and somewhat favorable. In this dataset, the network outperforms existing NN models like the RNN and the matrix-vector RNN with a test accuracy of 45.4%.

METHODOLOGY

The Deep learning-based CNN model is used to find the polarity of the textual data. The proposed work methodology is explained in this section. Figure 2 shows the proposed methodology where first the textual data is collected and prepared. Data cleaning is done as it is important to preprocess data and to remove unwanted information, notations, and punctuations and shorten the given text. For feature extraction, TF-IDF is used. To provide a comparable representation for terms with similar meanings, the words are then grouped. To build the representation, the word embedding learns the connections between the words. In sentiment analysis, this is referred to as embedding. Word, phrase, and document-level embedding are all done, among other levels of embedding. Finally, sentiment analysis uses a convolution neural network to assess the document's polarity.

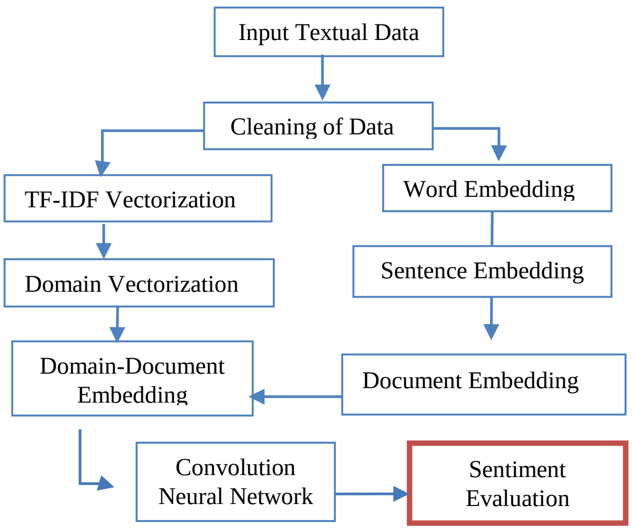

Figure 2. Proposed Methodology for SA

Text preprocessing is a crucial step in NLP tasks because it allows for the extraction of hidden sentiment from text data. In text preprocessing, collected raw text data only requires minor adjustments to transform it into a state in which DL algorithms could function more effectively. Text data has been cleaned by removing unnecessary words, unknown words, and symbols that won't be useful for training since it can't use text data directly for classification.[29] To get a sequence of numbers for each review and a word represented by a number, tokenization and padding are applied to clean text data. Positive sentiment is valued at one in this study, while negative sentiment is valued at zero. Because of its objectivity, neutral sentiment data is excluded from our dataset. If a review is longer than the maximum allowed, it will be cut off at the desired length from the back.

Study suggests a CNN-based model and assess its performance to determine the accuracy with which consumer-posted online reviews can be classified as either positive or negative. This study also applies several traditional ML models to the data gathered from various online sources, including airlinequality and Twitter, as part of that strategy. This study also compares the proposed model to applied conventional ML models. To ensure that the results are accurate and do not affect overfitting, validate obtained results using a suggested evaluation methodology in ML[30]

The proposed system architecture, which is depicted in Figure 2, is based on natural language processing tasks, and this includes all preprocessing and model training steps. This employ the classification models that our text datasets have already trained, choose the model with the highest accuracy, and make predictions using that model.

When training the various classification models, feature vectors are to be used as a representational strategy. The Term Frequency-Inverse Document Frequency (TF-IDF) method gives each word in a text a score based on how frequently it appears in the text as well as how likely it is to appear in texts belonging to other categories.[31,32] This implies that, regardless of their classification, words that appear often in texts are given a lower score. These feature vectors may now be used to train various classification models. It is a technique for removing characteristics from text data. IDF stands for Inverse Document Frequency, and TF stands for Term Frequency.[33] The TF-IDF vectorizer stands for inverse document frequency (IDF) and term frequency (TF). This measurement's mathematical equation is [13]:

$$tfidf(t,d,D) = tf(t,d) X\ idf(t,D)$$

Where t: terms, d: document, D: a collection of documents.

The Term Frequency TF measures the number of times each word appeared in each document, TF is defined as:

$$tf(t,D) = \frac{Count(t)}{Mod\ Di}$$

Where count (t) denotes the term's frequency and Mod Di is the total number of words in the document Di. Inverse Document Frequency, on the other hand, is used to identify whether a phrase is frequent or uncommon throughout a dataset. Compared to words that are used seldom, common words are less valuable. This is how the IDF is described:

$$idf(t,D) = \frac{Mod\ D}{1 + |\{d \epsilon D: t \epsilon d\}|}$$

Mod D: the size of the document space, $|\{d \epsilon D: t \epsilon d\}|$: represents the number of times the term has appeared in document d.

Convolutional neural network (CNN) provides the foundation for another component of our proposed system. In recent years, CNNs have been particularly effective for a variety of computer vision and NLP applications. They are particularly adept at making use of the local correlation and pattern in the data that their feature maps have learned which demonstrated excellent performance on several text classification problems and utilized CNN for text classification.[34] The embeddings from the various words in a sentence (or paragraph) are often stacked to create a two-dimensional array before convolution filters (of various lengths) are used to create a new feature representation on a window of h words. The pooled features from various filters are then added together to create the concealed representation after some pooling (often max-pooling) has been performed on the new features. One (or more) fully connected layer(s) are then applied to these representations to get the final prediction.

The Cleaning Procedure for Sentimental Analysis is shown in Figure 3. The cleaning procedure entails four steps.

- Filtering: this involves deleting URL linkages, such as http:Google.com, as well as tags to other accounts, which often start with the @ sign on Twitter.
- Eliminating commas, period, and articles, as well as prepositions such as the, an, and the Because these symbols, are useless for our approach, Punctuations Removal seeks to eliminate punctuation marks like {#,-,_,,,,;,:,‘}
- Lower-case transformation is done, then there are three processes. All data should be converted to lowercase as this will aid in preprocessing and subsequent parsing phases of the NLP application.
- The next phase, known as tokenization, is creating a bag of words by eliminating any punctuation or question marks. As a result, huge volumes of data can be properly represented.

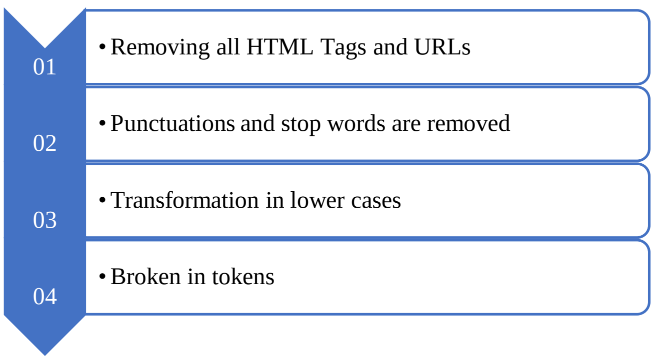

Figure 3. Cleaning Process for Sentimental Analysis

This study may go on to additional analysis by dividing texts into tokens after cleaning up the text documents. The embedding process transforms these tokens into feature vectors.

Words must first be converted into numbers to be used in a classifier. Simply mapping words to numbers is one method to do this. One such approach is to one-hot encrypt words. Then, for each tweet, a vector with a dimension equal to (a constrained set of) the words in the corpus might be used to represent it. The vector has a value of 1 for the terms that appear in the tweet. Zero is equivalent to all other vector values.

The computation of document embeddings varies. A multi-dimensional space is used to locate each word. A word's location in this embedding space is represented by its vector values. When compared to terms with opposing meanings, synonyms are often found close together.

The Document Embedding for Sentimental Analysis is shown in Figure 4. It also includes a few stages, which are described below:

Word2vec: A collection of algorithms called Word2vec produce word embeddings as numerical vectors. By calculating the distance between the related vectors in this space, it is possible to identify how similar a word is to other words in the dataset. The basic concept is to leverage the context of nearby words to find words that are similar depending on how they are represented in the vector space.[35] Word2vec produces one vector for each word, in contrast to word count and TF-IDF. Examining papers and determining their contents is highly helpful.

SkipGram: One unsupervised learning method used to discover the words that are most connected to a given word is the skipgram. To determine the context word for a given target word, skip-gram is employed. It is the CBOW algorithm inverted. Here, the target word is entered and the surrounding words are produced.[36] When given a current word, the continuous skip-gram model learns by predicting the words that will be around it. To put it another way, the Continuous Skip-Gram Model foretells words that will appear before and after the present word in the same phrase within a certain range. The Continuous Bag of Words makes word predictions given nearby context. The skipgram predicts the context or nearby words for a given word, as seen in the architecture above. The (target word, context word) n-gram pairings with a token as 1 and 0 are used to train the Skip-Gram model. The token indicates whether the context words were created randomly or from the same window. Neglected is the pair with token 0.

Sentence Embedding: Using merely words in a huge text would be incredibly time-consuming, and the amount of data could glean from the word embeddings would be constrained. Techniques for sentence embedding portray full sentences and the semantic information they include as vectors. This aids the machine's comprehension of the full text's context, purpose, and other subtleties. Similar to word embedding, sentence embedding is a highly prominent topic of study with cutting-edge methods that assist machines to comprehend human language. Each phrase has a term frequency or co-occurrence matrix, which was previously covered before.

Document Embedding: Similar to sentence embedding, the whole text is applied using term frequency or co-occurrence matrix. The process of discretely approximating word embeddings is also known as document embedding. This has trouble establishing the contextual link between the words in vector form since word embedding approximation or learning transforms the whole corpus into vectors. Establishing the contextual associations between words is possible by extracting tiny corpora and turning them into vector representations.

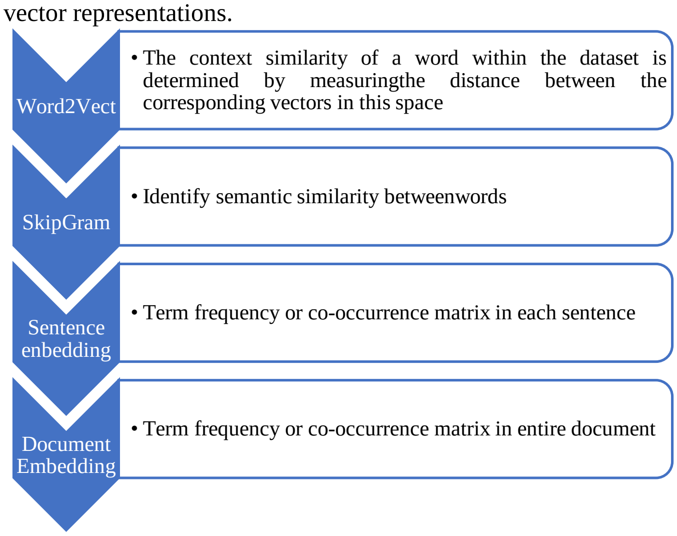

Figure 4. Document Embedding for Sentimental Analysis

Result And Discussion

This paper has implemented and trained the models in the Keras framework with TensorFlow. The proposed model was trained

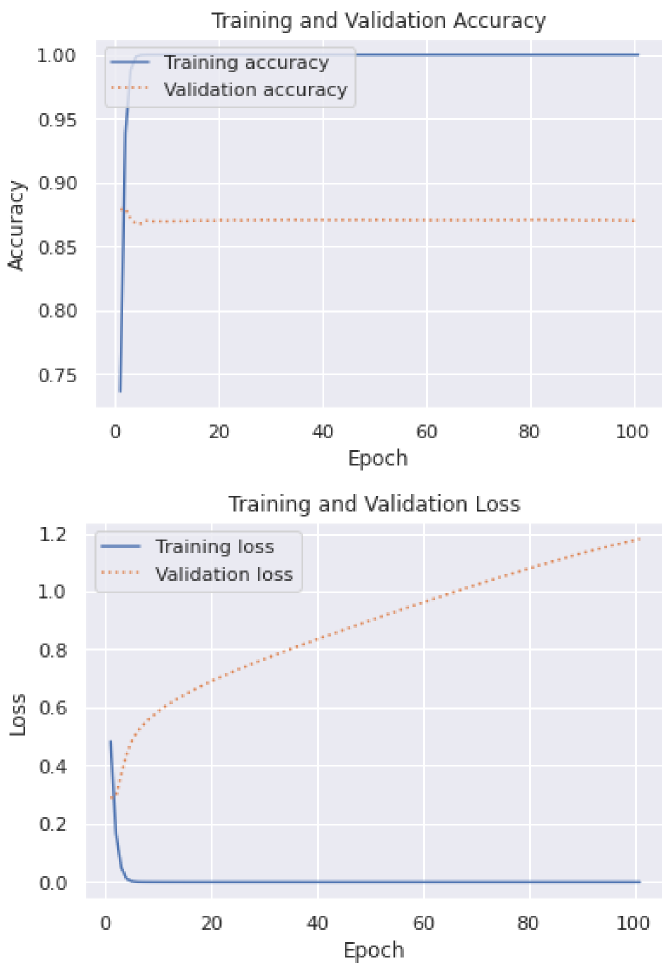

Figure 5. Training Accuracy and Loss Graph

Table 1. Comparative State of Art

Technique	Accuracy
SVM+LSTM [19]	73.81%
CNN [20]	68.7%
BiLSTM [21]	72.25%
DL-LSTM [23]	86.03%
SVM [26]	83%
Word2vec + CNN [28]	45.4%
Ours	87%

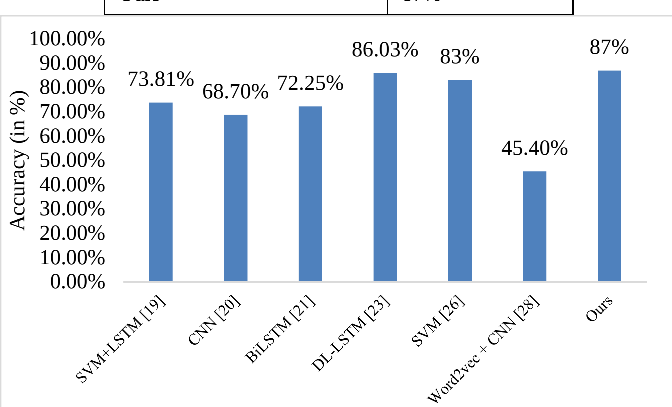

Figure 6. Comparative State of Art

using GPU on google colab. The following performance parameters are used to evaluate the model's efficiency in terms of Accuracy, precision, and recall.

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

Where, TP= True Positive, FP= False Positive, FN= False Negative and TN = True Negative

n Figure 5, training accuracy and training loss graph is represented. The accuracy graph is plotted between epoch and training and validation accuracy and shows that when the value of Epoch is at 0.50 the training and accuracy values are at 1.00 and 90. And loss graph is plotted between Epoch and training and validation loss shows that when the epoch value the training loss is 0.4 and the validation loss is 0.98. The graph represents better convergence of accuracy and loss towards solution. But in validation, the convergence of loss was not good. This will result is lower accuracy and can be considered as future work scope.

Table 1 shows the comparative state of the art of various techniques where the accuracy of our proposed model is compared with SVM+LSTM, CNN, BiLSTM, DL-LSTM, SVM, Word2Vec+CNN and ours having accuracy 73.81, 68.7, 72.25%, 86.03%, 83%, 45.4%, and 87% respectively. According to figure 6, it is inferred that the proposed algorithm has achieved highest accuracy as compared to state-of-art models.

Conclusion

Communication patterns have drastically altered because of social networks. Data, Information, and Content from various social media sites may be effectively used to analyze user opinions. Therefore, the creation of a system that can assess consumer perceptions of their goods and services in social media will be advantageous to the companies and add quality to their operations. Deep learning has gained a lot of traction in the previous few years in fields like speech recognition and image classification. The application of DL to SA has, nevertheless, received minimal research. It's been noted that the present ML algorithms for SA may not be very useful and may miss several underlying components. In process of extracting elements from documents and analyzing user sentiment for all those characteristics, we recommend a DL technique. Deep convolutional neural networks are used to tag every element of the opinionated remarks. Additionally, study looked for ways to enhance the current strategy and contrasted our suggested approach with certain cutting-edge techniques. It has been noted that the overall accuracy of our suggested technique is 0.87. The overall accuracy of our suggested technique is 1-2% higher than that of the most recent methods. The future of sentiment analysis will include digging even farther under the surface of likes, comments, and shares to properly grasp the value of social media interactions and what they reveal about the people who use the platforms. This projection also forecasts that sentiment analysis will have more widespread uses in the future. In addition to businesses, this technology will also be used by public figures, governments, NGOs, educational institutions, and a variety of other organizations.

CONFLICT OF INTEREST

Authors do not have any confict of interest for this work.

LIST OF ABBREVIATIONS

SA	Sentiment Analysis
SVM	Support Vector Machine
NLP	Natural Language Processing
ML	Machine Learning
DL	Deep Learning
LSTM	Long Short Term Memory
BiLSTM	Bidirectional LSTM
CNN	Convolution Neural Network
TFIDF	Term Frequency-Inverse Document Frequency

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