International Journal of Modern Computation, Information, and Communication Technology
2023;6(1):12-17.
ISSN: 2581-5954

Sentiment Analysis Using Deep Learning Techniques

B. Praveen Kumar[1*], J. Umamageswaran[2], A.V. Kalpana[3], R. Dhanalakshmi[4]

[1]*Department of Computer Science and Engineering, Sri Venkateswara College of Engineering, Sriperumbudur, Tamil Nadu, India.*
[2]*Department of Information Technology, R.M.K Engineering College, Kavaraipettai, Chennai, Tamil Nadu, India.*
[3]*Department of Artificial Intelligence, Shri Vishnu Engineering College for Women, Bhimavaram, Andhra Pradesh, India.*
[4]*Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India.*

[*]*Corresponding author: bprawinkumar@gmail.com*

Abstract. Massive troves of information, including users' perspectives, feelings, ideas, and disputes regarding various social events, goods, brands, and politics, are produced by various online platforms, such as social networks, forums, review sites, and blogs. Readers, product sellers, and legislators all pay close attention to the opinions offered by internet users. Sentiment analysis has garnered a lot of interest because of its ability to evaluate and organize the unstructured type of data seen in social media. The term "sentiment analysis" is a method of text organization used to categorize the conveyed mindset or emotions as either "negative," "positive," "neutral," "positive," "negative," "thumbs up," "thumbs down," etc. The difficulty with sentiment analysis is that there is not enough labeled data in the NLP sector. Since deep learning models are useful because of their automated learning potential, this problem has been solved by combining sentiment analysis with deep learning. The current research on using deep learning models like deep neural networks to address sentiment analyzing challenges such as sentiment categorization, cross-lingual issues, textual/visuals analysis, product reviews analysis, etc., are summarized.

Keywords: Sentiment analysis, Deep Learning, Social Networks, and NLP

INTRODUCTION

Facial expression analysis has been studied extensively for its applications in social sciences and human-computer interactions. Improvement in this domain has been made possible by deep learning that surpasses the human level of accuracy. In this piece, we'll go over some of the most widely used deep learning algorithms for emotion identification, as well as how to increase their accuracy by using the event library. However, there is still more work to be done in the areas of memory and computing. Overfitting becomes problematic in very big models. The generalization error may be reduced as a means of overcoming this challenge. To build a new CNN model with parallel feature extractions, we use a custom-made Convolutional Neural Network (CNN) known as eXnet. Newer eXnet (Expression Net) models are more accurate than their predecessors while requiring fewer inputs. The generalized event takes advantage of data augmentation methods that have been used for decades. Over fitting is effectively mitigated, and the overall size is kept in check [1]. It is of interest to social scientists and psychologists to learn how individuals react emotionally and psychologically to catastrophic occurrences like natural catastrophes, political unrest, and acts of terrorism. Depression and other mental health problems have arisen because of the COVID-19 epidemic, which has caused rapid societal shifts and a loss of jobs.

Promising developments in deep learning-based languages model for sentiment analysis using social networks like Twitter have been made. Since the number of COVID-19 cases spiked and then dropped at various times in different nations, the economy and the number of people working in those countries were both negatively impacted [2]. More COVID-19 instances have led to more stringent lockdowns, and individuals have begun voicing their feelings online. This may help us better comprehend the human psyche in the face of calamity. In this study, we provide a methodology for sentiment analyses during the recent outbreak of a unique COVID-19 case in India using a deep learning-based language model implemented as long short-term memory (LSTM) recurrent neural network. The advanced BERT languages models and the LSTM languages models with global vector embedding are both part of the system. We look at how people feel during the peak months of new cases in India in 2020 [3].

Received: 10.12.2022 Revised: 02.02.2023 Accepted: 17.02.2023

Since it is possible to convey many emotions simultaneously, our approach makes use of multi-label sentiment categorization. Our findings show that as the number of reported instances of the new COVID-19 increased, the number of tweets on the topic decreased dramatically. Positive, irritated, and humorous tweets far outnumber those with a negative tone by a wide margin each month. Predictions suggest that most people are hopeful, but sizeable minorities are frustrated with the government's response to the epidemic [4]. Since the appearance of the coronavirus, genuine clinical resources, such as a dearth of experts and healthcare workers, inadequate equipment and medications, etc., have reached crisis levels of accessibility. There is widespread anxiety within the medical community, leading to the premature deaths of many professionals. Patients' health conditions worsened as they began self-medicating in response to drug shortages rather than seeking professional advice. Recently, there has been a rise in creative work for automation [5], and machine learning has proven useful in several contexts.

LITERATURE SURVEY

In recent years, there has been a significant increase in regional language content online. It breaks down linguistic boundaries, allowing individuals to speak their minds. There are 170.2 million native speakers of Urdu. To get an understanding of public sentiment, sentiment analysis is used. There has been a rise in recent years in the number of studies focusing on Urdu sentiment analysis. Few studies have looked at how deep learning may be used for Urdu sentiment analysis. Due to its morphological complexity, texts processing in Urdu is a significant challenge. Here we offer a framework for Urdu Text Sentiments Analysis (UTSA) by investigating deep learning strategies in tandem with several different word vector representations [6]. For this purpose, we assess the efficacy of several deep learning approaches, including Long Short-Terms Memory (LSTM), attentions-based Bidirectional LSTM (BiLSTM-ATT), Convolutional Neural Network (CNN), and CNN-LSTM. The LSTMs, BiLSTM-ATTs, and C-LSTMs sequential models all use stacked layers.

Multiple filters are used in a single convolution layer to create CNN. The task of sentiment categorization is used to examine the effectiveness of both supervised and unsupervised methods of training embedding models. The collected findings demonstrate that the BiLSTM-ATT achieved 77.9% accuracy and 72.7% F1 score [7], which is higher than the results produced by other deep learning models. Natural language processing (NLP) is the process of representing human languages automatically using a variety of methods. Graph, deep neural networks, and word embedding are just a few of the technologies that may be used to enhance NLP applications. An essential part of sentiment analysis is sentiment classifications, which aim to automatically categorize opined material as positives, negatives, or neutrals. This review [8] examines the development of deep learning-based sentiment analysis techniques during the last five years.

Health concerns have been raised on a global scale due to the proliferation of Covid-19. More people are discussing it and sharing their thoughts on it through social media. To make the best and most efficient use of available resources, a sober evaluation of the situation is required. We use supervised machine learning to analyze the tone of tweets from the Covid-19 conference. To better deal with the present pandemic scenario, it would be useful to be able to identify Covid-19 attitudes from tweets. The Twitter IDs used to extract information are made available through the IEEE data port. The Tweepy library [9] is used by an in-house developed crawler to extract tweets. Following preprocessing approaches, the dataset is ready for sentiment extraction with the help of the TextBlob toolkit. The examination of the performances of several machine learning classifiers using our suggested feature set is the main contribution of this study. Bag-of-word and terms frequencies inverse documents frequency are joined to generate this collection. There is a good, neutral, and negative category for tweets. Accuracies, precisions, recall, and F1 scores are used to assess classifier performances [10].

Long Short-Terms Memory (LSTM) is included in the deep learning model's architecture to do more research on the dataset. We suggested concatenated feature sets allow Extra Tree Classifier to surpass all other models with an accurate score of 0.93. When compared to other machine learning classifiers, LSTM’s performance is subpar. We compare our findings with those obtained using the Vader sentiments analysis method, which is based on the GloVe feature extractions strategy [11], to show the efficacy of our suggested feature set. In this study, we provide a comprehensive analysis of deep learning approaches to Sentiments Analysis. One of the most studied subfields in NLP is sentiment analysis. Voice recognition, machine translations, product reviews, aspect-oriented product analysis, sentiment analysis, and text classifications (including email categorizations and spam filtering) are just a few of the many uses for NLP. Lexicon-based processing is the standard approach used when doing sentiment analysis. However, with the development of AI, machine learning algorithms have become more important in sentiment analysis [12].

The use of deep learning as a means of predicting emotions is the current buzzword in the field. Several studies using deep learning techniques have been conducted in the field of Natural Language Processing (NLP). In the realm of deep learning, Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in particular Long Short Terms Memory (LSTM) models, are especially popular. Depending on the specifics of the domain at hand, these methods may be employed in tandem with one another or independently. This review concentrates on the many forms that deep learning approaches to sentence-level and aspect/target-level sentiment analysis take. Parameters of performance, as well as the approaches' benefits and downsides, are reviewed [13]. Online opinion mining and sentiment analysis of texts has recently attracted the interest of government, business, and academia in response to the explosion of social media information on the web.

Sentiment analysis has recently been a major study issue in the fields of artificial intelligence and machine learning, as well as having evolved under knowledge fusions in the big data age. The biggest online forum in Taiwan, Military Life PTT, was mined for experimental data in this research [14]. The goals of this research were to evaluate the efficacy of various deep learning models with a wide range of parameter calibration combinations and to propose self-developed military sentiment dictionaries to aid in sentiment classifications. The accuracy and F1-measure of the model that incorporates both publicly available sentiment dictionaries and custom-built military sentiments dictionary outperform those of the model that utilizes solely publicly available sentiment dictionaries, as shown by testing findings. Additionally, when the numbers of the Bi-LSTM networks layer are set to two, the accuracy and F1-measures have even higher performances for sentiment classifications [15]. This is because the predictions model is trained using the Tanh activations functions.

PROPOSED SYSTEM

The research communities lost interest in neural networks in the late 1990s because training a "deep" neural network (one with three or many layers) is difficult and measurably very costly, making "shallow" networks (those with one or two layers) more appealing. However, deep learning has made significant progress and generated advanced results across a wide range of application domains in the last decade, first in computer vision, then in voice recognition, and most recently in natural language processing. There are several causes for the recent popularity of neural networks. Some of the most significant include the increased computer power made possible by technological advancements (e.g., GPU), the abundance of available training information, and the effectiveness and adaptability of learning intermediates representation. To summarize, deep learning employs a hierarchy of nonlinear processing units to extract and manipulate features. Simple characteristics are learned by the layers closest to the data input, whereas more complicated features are learned by the layers further up.

The structure creates a robust and hierarchical feature representation. In Figure 1, we can see how deep learning for a face picture classification elicits a feature hierarchy from lower to higher layers. We can observe that the complexity of the learned picture characteristics increases from blob/edge to noses/eyes/cheekbones to whole faces. Deep learning models have shown considerable promise in natural language processing (NLP) in recent years. We provide a high-level overview of the most prominent deep learning architecture and associated approaches that have been applied to NLP applications in the following sections. Word embedding findings are used as input features by several deep learning models in natural language processing. To better understand languages and learn their features, researchers developed a method called "word embedding," which maps words to vectors of continuous real numbers. Typically, the method entails embedding data from sparse vector spaces (such as one-hot encoding vector spaces, where each word is a dimension) into dense vector spaces with fewer dimensions. Figure 1 shows the system architecture of the proposed system.

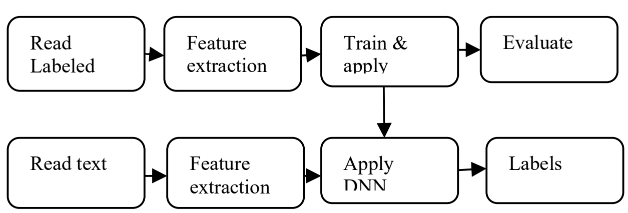

FIGURE 1. System architecture of the proposed system

The CBoW models predict the target's word (such as "wearing") given the word around it (such as "the boy is a hat," where "_" signifies the target's words), whereas the SG models do the opposite. By considering the whole set to be a single observation, the CBoW model statistically flattens a considerable quantity of distributional information. It works well on tiny datasets. On the other hand, the SG models consider each context-target combination to be separate observations, making it more suitable for bigger datasets. Global Vectorii is a popular learning method that is learned using a global word-word co-occurrence matrix with non-zero elements. We may now begin our overview of deep learning's use in opinion mining. But before we get into it, let's take a quick look at the most common applications of sentiment analysis. Liu's book on sentiment analysis is a good resource for further information. Sentiment analysis has mostly been explored at the document, phrase, and aspect levels by academics. Classifying the overall positive or negative tone of an opinionated text (like a product review) is the goal of document-level sentiment classification. It treats the whole text as the fundamental unit of data and presupposes that it is opinionated and contains thoughts on a single thing (such as a certain phone). The emotion of a paper may be broken down into sentences and categorized separately. However, not every statement should be interpreted as having an opinion.

Subjectivity categorization, the conventional starting point, involves labeling a text as opinionated or non-opinionated. The resultant phrases represent views, which are then categorized as favorable or negative. Classifying the emotional tone of a statement may be seen as a classification issue with three classes: neutral, positive, and negative. Sentiment analysis at the aspect level, sometimes called aspect-based sentiment analysis, is more nuanced than analyses conducted at the documents and sentences levels. Its job is to sift through user reviews of entities and the attributes and characteristics of those entities (together referred to as "targets") and then summarize those reviews. Even whether the overall evaluation of the product is favorable or negative, a review's goal is to outline the pros and cons of the product in terms of specific areas. Aspects extractions, entity extractions, and aspects sentiments classifications are all parts of the larger problem of aspect-based sentiment analysis. The line "the voice quality of iPhone is great, but its battery sucks" has two aspects: "voice quality" and "battery," therefore entity extractions should determine that "iPhone" is the entity in this case, and "aspect extraction" must determine that "voice quality" and "battery" are two of the aspects. The opinions stated about the iPhone's voice quality should be labeled as good, while those about the iPhone's battery life should be labeled as negative, according to the aspect sentiment categorization. You should know that most algorithms combine extractions and entity extractions into a single process. They call aspects extractions or sentiments/opinions targets extractions since it's easier to explain. Sentiment analysis goes beyond these central functions by exploring related topics such as emotions analysis, sarcasm detection, multilingual sentiment analysis, and so on. Here, we look at how deep learning has been used in various sentiment analysis tasks.

RESULTS AND DISCUSSIONS

The importance of word embeddings in deep learning-based sentiment analysis models is undeniable. Word embeddings are demonstrated to be useful as a feature for non-neural learning models for a variety of tasks, and this is true regardless of whether deep learning models are used. The significance of word embeddings in sentiment analysis is therefore emphasized in this section. Sentiment-encoded word embeddings are introduced initially. The difficulty with using regular words technique like CBoWs or Skip-grams to train word embedding from contexts for sentiments analysis is that words with similar context but opposing sentiments polarity (such as "good" or "bad") might be mapped to close vectors in the embedding's spaces. Figure 2 shows the accuracy of the proposed system.

Word embedding that can capture both semantics and sentiment information has been developed; these are called sentiment-encoded word embedding approaches. Re-embed current word embedding using logistic regressions thinking of sentiments supervisions of the sentence as a regularization's terms; this research demonstrated that n-gram models paired with latent representations would provide a more acceptable embedding for sentiments classifications. A paragraph vector was proposed as a means of first mastering a fixed-length representation for texts with varying sentence, paragraph, and document lengths. They conducted experiments on sentence- and document-level sentiment classifications tasks and found improvements in performances, showing the value of paragraphs vector in capturing semantics to aid sentiment classifications. They also presented a model to learn sentiments-specific word embedding (SSWEs), in that not only the semantics but also sentiments data is embedded in the learning words vector. A refining technique to acquire word vectors that include both semantic and sentimental information is utilized. The use of multi-sense word embeddings and feature enrichment in sentiment analysis is also explored.

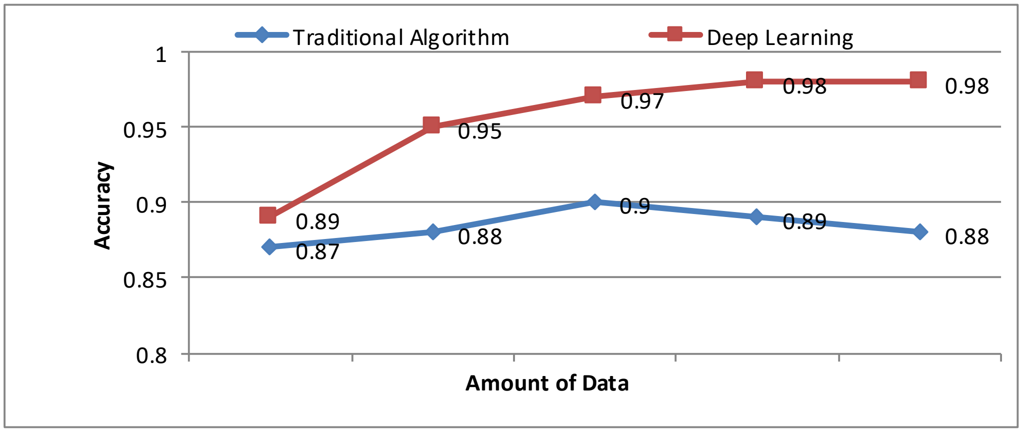

FIGURE 2. Accuracy of the proposed system

Experimented with the usage of multi senses word embedding on a variety of NLP tasks, studied aspect-based Twitter sentiment categorization utilizing rich automated features (additional feature produced using unsupervised learning approaches). The suggested approaches to train topic-enriched multi prototypes word embedding for Twitter sentiment classifications have been tested, and although they do enhance the performance of certain tasks, they give little support to sentiments classifications tasks. Sentiment analysis is another area where multilingual word embedding has been used. To classify emotion across languages, researchers have reported a "bilingual sentiment word embedding" (BSWE).

Rather than using massive parallels corpora, it uses labeled corpora and their translations to add sentiment information into English Chinese bilingual embedding. Contrasted several forms of neural machine translations and word embedding for cross-lingual aspect-based sentiment classification: combined word embedding with matrix factorizations for individual review-based ratings predictions. This paper proposes a semi-supervised method for leveraging sentiment-bearing word embeddings to rank the emotional intensity of adjectives, and it does so by refining current semantic-oriented word vectors (such as word2vec and GloVe) with sentiment lexicons. There has also been some work on using and enhancing word embedding methods to aid sentiment analysis.

CONCLUSION

Deep learning models are more accurate than shallow models since they focus on prediction or mimicry of the human mind, while sentiment analysis is used to forecast user opinions. Because deep learning networks have more hidden layers than SVMs and standard neural networks, which only have one or two, are superior to those two types of networks. Both supervised and unsupervised training can be delivered by deep learning networks. Deep learning networks automatically extract features without human involvement, which saves time because feature engineering is not required. Different types of problem statements are included in sentiment analysis. One advantage of deep learning is its capacity to adapt to changing tasks by making only minor changes to the system itself. In comparison to earlier models like SVM, this technique also has significant drawbacks. It is quite expensive to train and needs a lot of data. Utilizing pricey GPU-equipped PCs, these complicated models can be trained over the course of weeks.

REFERENCES

[1]. K. Kottursamy, 2021, "A review on finding an efficient approach to detect customer emotion analysis using deep learning analysis," *Journal of Trends in Computer Science and Smart Technology*, **3(2)**, pp. 95-113.

[2]. R. Chandra, A. Krishna, 2021, "COVID-19 sentiment analysis via deep learning during the rise of novel cases," *PloS one*, **16(8)**, pp. 1-15.

[3]. S. Garg, 2021, "Drug recommendation system based on sentiment analysis of drug reviews using machine learning," *11th International Conference on Cloud Computing, Data Science & Engineering*, pp. 175-181.

[4]. U. Naqvi, A. Majid, SA. Abbas, 2021, "UTSA: Urdu text sentiment analysis using deep learning methods," *IEEE Access*, **9**, pp. 114085-114094.

[5]. W. Etaiw, D. Suleiman, and A. Awajan, "Deep learning-based techniques for sentiment analysis: A survey," *Informatica*, **45(7)**, 2021

[6]. W. Van Atteveldt, MA. Van der Velden, and M. Boukes. 2021, "The validity of sentiment analysis: Comparing manual annotation, crowd-coding, dictionary approaches, and machine learning algorithms," *Communication Methods and Measures*, **15(2)**, pp.121-140.

[7]. J.Z Zhang, PR. Srivastava, D. Sharma, and P. Eachempati, 2021, "Big data analytics and machine learning: A retrospective overview and bibliometric analysis," *Expert Systems with Applications*, **184**, pp. 1-24.

[8]. F. Rustam, M. Khalid, W. Aslam, V. Rupapara, A. Mehmood, and GS. Choi, 2021, "A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis," *Plos one*. **16(2)**, pp. 1-9.

[9]. C.N. Dang, MN. Moreno-García, and F. De la Prieta, 2021, "Hybrid deep learning models for sentiment analysis," *Complexity*, **2021**, pp. 1-6.

[10]. AE. de Oliveira Carosia, GP. Coelho, and AE. da Silva, 2021, "Investment strategies applied to the Brazilian stock market: a methodology based on sentiment analysis with deep learning," *Expert Systems with Applications*, **184**, pp. 1-15.

[11]. S.A. Abdu, A.H. Yousef, and A. Salem, 2021, "Multimodal video sentiment analysis using deep learning approaches and a survey," *Information Fusion*, **76**, pp. 204-226.

[12]. M.M. Rahman, and M.N. Islam, 2021, "Exploring the performance of ensemble machine learning classifiers for sentiment analysis of COVID-19 tweets," *in Sentimental Analysis and Deep Learning: Proceedings of ICSADL*, pp. 383-396.

[13]. E. Elgeldawi, A. Sayed, AR. Galal, and AM. Zaki, 2021, "Hyperparameter tuning for machine learning algorithms used for Arabic sentiment analysis," *In Informatics Multidisciplinary Digital Publishing Institute*, **8(4)**, pp.1-15.

[14]. I. Aygün, B. Kaya, and M. Kaya, 2021, "Aspect-based Twitter sentiment analysis on vaccination and vaccine types in the COVID-19 pandemic with deep learning," *IEEE Journal of Biomedical and Health Informatics*, **26(5)**, pp. 2360-2369.

[15]. H. Li, Y. Ma, Z. Ma, and H. Zhu, 2021, "Weibo text sentiment analysis based on Bert and deep learning," *Applied Sciences*. **11(22)**, pp. 1-17.