Transforming Sentiment Analysis Using Deep Learning Approaches: A Review

*Ronit Raj[1], Navneet Kaur[2] and Paurav Goel[3]

[1,2,3]Department of CSE, Chandigarh University, Punjab, India

[1]ronitraj9211@gmail.com, [2]navneetsehgal5@gmail.com,
[3]pauravg5986@gmail.com

Abstract. In the age of digital transformation, vast amounts of textual data are generated every second across social media, e-commerce platforms, and other online forums, making the recognition and interpretation of sentiments within this data increasingly critical. The goal of SA (Sentiment Analysis), a subfield of NLP (Natural Language Processing), is to find and extract subjective information from written material, with uses spanning from brand tracking to forecasting stock market trends. Traditional methodologies, which rely on lexicons and statistical models, have demonstrated limited scalability and adaptability when dealing with the complexities of human communication. Deep learning has revolutionized sentiment analysis by developing algorithms capable of detecting complex language patterns and contextual interactions. Models such as CNNs (Convolutional Neural Networks), RNNs (Recurrent Neural Networks), and advanced designs like Transformer-Based Bidirectional Encoder Representations BERT have transformed the field due to their remarkable accuracy and efficiency. This study explores the evolution of sentiment analysis techniques, focusing on the transformative power of deep learning models. It analyzes their applications across a wide range of datasets, showing their advantages over traditional techniques while also critically assessing the challenges they encounter, including as processing requirements and interpretability difficulties. This study aims to provide an extensive review of deep learning-based sentiment analysis DL-SA, identify research gaps, and suggest future avenues for exploration. For researchers and professionals hoping to use DL (Deep Learning) for SA (Sentiment Analysis) in a world that is becoming more and more data-driven, this paper is a great resource.

Keywords: Sentiment analysis (SA); Recurrent neural network (RNN); Deep neural network (DNN); Convolutional neural network (CNN); Recursive neural network (RNN); Deep belief network (DBN).

N. Vyas et al. (eds.), *Proceedings of the International Conference on Advancements in Computing Technologies and Artificial Intelligence (COMPUTATIA 2025)*, Advances in Intelligent Systems Research 189,
https://doi.org/10.2991/978-94-6463-700-7_7

1 Introduction

1.1 Sentiment Analysis (SA)

Sentiment analysis involves handling subjective text, emotions, and viewpoints [1]. Sentiment analysis provides valuable insights into public sentiment by analyzing reviews, tweets, and other forms of user-generated content. This method accurately predicts significant events like elections and movie box office [2]. People, goods, and locations are criticized in public reviews on websites such as Yelp and Amazon. One could categorize the opinions as neutral, positive, or negative. User reviews' expressive direction is automatically determined by sentiment analysis [3]. When it comes to organizing and analyzing unstructured social media data, sentiment analysis is becoming important [4].

1. **Sentiment analysis features include.** Sentiments use polarity and combination to incorporate emphasized values, such as Bigrams and Trigrams. Support vector machines and training methods are used to evaluate sentiments, both positive and negative. To determine if labels belong together, sentiment analysis uses neural networks. By employing conditional interactions between nodes and edges in an acyclic graph, Bayesian networks are able to extract data at the context level. Optimizing words and phrases improves the accuracy of data on social networking sites. Word root tokenization yields both positive and negative data. In social media, methods are employed to improve data accuracy and remove sentiment analysis flaws [5].
2. **Sentiment Analysis as a Multidisciplinary Field.** Sentiment analysis integrates various components, including Natural Language Processing (NLP), Machine Learning (ML), Information Retrieval, Computational Linguistics, and Artificial Intelligence [6]. Three levels can be used to categorize sentiment analysis: feature/aspect, document, and sentence [5].
3. **Techniques for Sentiment Analysis (SA):** Sentiment analysis typically employs two main approaches: lexicon-based and machine learning-based methods [5].
   a) ***Machine Learning-Oriented Techniques.*** These methods include sentence extraction and aspect-level analysis, utilizing features such as POS tags, n-grams, bigrams, unigrams, and the bag-of-words model.
   b) ***Lexicon-Oriented Methods***. Sentiment classification algorithms often use decision tree-based methods like k-nearest Neighbors (k-NN), along with techniques such as Conditional Random Fields (CRF), Sequential Minimal Optimization, and Hidden Markov Models.

There are three main forms of machine learning: supervised, semi-supervised, and unsupervised. This method is highly effective for sentiment analysis as it is automated and capable of processing massive amounts of information [6].

1.2 Deep Learning (DL)

ML technique based on deep neural networks is called "deep learning." It was first offered with the aid of G.E. Hinton in 2006 [7]. These networks, which are made up of several linked neurons that shape an extremely complex device, had been stimulated by using the structure of the human brain. each supervised and unsupervised strategy may be used to train deep learning models [8]. Deep learning networks, including CNN, RNN, Recursive Neural Networks, and (DBN), are widely used for various tasks. Sentence categorization, feature representation, word embedding estimates, vector representation, text creation, and sentence modeling are a few examples [9].

- **Deep Learning Uses:** The architecture consists of multiple nonlinear layers. The capability of deep architectures to address complex AI problems suggests their effectiveness in tasks like semi-supervised learning, such as (DBN), and natural language processing [10]. Deep learning is oriented on improved software engineering, advanced learning algorithms, and sufficient processing power along with access to large training datasets [11].

Deep learning architecture needs a high number of labeled samples in order to acquire data for varied applications. Deep learning networks and algorithms are widely employed in a variety of fields; these include tasks like optical categorization, off-road robot navigation, and pedestrian detection, object classification, acoustic signal processing, and time series prediction [13]. An essential method for natural language processing [13] suggests that deep structures are well-suited to handle complex multitasking, such as semantic labeling. Deep learning employs hierarchical systems to extract high-level abstractions from data. This powerful approach has become widely adopted in domains of artificial intelligence, including natural language processing, transfer learning, computer vision, and semantic parsing. Its growing popularity is attributed to enhanced GPU processing power, reduced hardware costs, and advancement in (ML) framework [14].

1.3 Integrating Deep Learning (DL) and Sentiment Analysis (SA)

(DL) has a significant impact on both supervised and unsupervised learning on both sides, and many scholars apply it to sentiment analysis. It offers common models to effectively address a wide range of situations [15]. Socher's most well-known, for instance, uses a Recursive Neural Network (RNN) to represent movie ratings from Rotten Tomatoes.com [16]. Neural networks have been used in several research to classify sentiment, building on the work of [17]. Kalchbrenner proposed a Dynamic Convolutional Neural Network (DyCNN) that processes linear sequences using dynamic k-max pooling [18]. CNNs were used by Kim [19] to train sentiment-capturing text vectors.

The Paragraph Vector, which was first presented by [20], performs better in sentiment-specific word embedding (SSWE) than ConvNets and the bag-of-words model. Recently, [21] applied ConvNets to characters instead of word embeddings. The LSTM, a model used for sentiment classification, only requires a single input direction [22]. This study is divided into three sections: a thorough literature review in Section II, a conclusion in Section III, and an analysis of the review in Section IV. The Literature Review section discusses numerous publications on sentiment analysis with Deep Learning systems. This review looks at recent studies in sentiment analysis.

2 Literature Survey

Recently, researchers employed deep and machine learning concepts to effectively categorize sensations. This section is brief. Several studies have employed deep learning techniques to assess user thoughts, sentiments, and evaluations about numerous topics and products. Deep learning algorithms, which have recently been improved, may be useful in sentiment analysis jobs. The models used in sentiment analysis comprise (CNN), recursive neural networks, (DNN), recurrent neural networks, and (DBN). This specific section provides an overview of the efforts of several scholars who have applied deep learning models to sentiment analysis [23]. Several have utilized multiple models in their studies, which are detailed in the hybrid neural network section.

2.1 Convolutional Neural Networks (CNN)

The (CNN) [24] transforms variable-length words into fixed-size, sparse vectors using pooling layers and a standard topology. This research [25] introduces an architecture for a convolutional neural network (CNN) intended to predict sentiments in visual data. On a Linux computer, CNN was implemented using Caffe and Python. Biases were discovered utilizing a transfer learning approach, hyper-parameters, and pre-trained GoogLeNet weights. To enhance CNN performance, we propose 22 layers in a deep CNN model, built on GoogLeNet, for sentiment analysis. The SGD approach is used to optimize. The network was trained with a 60-epoch approach, whereas GoogLeNet required 250 epochs. To conduct tests, a Twitter dataset of 1269 images is chosen and backpropagation is employed. Amazon Mechanical Turk is used to annotate the photographs (MTurk) and widely recognized crowd intelligence. Each image was labeled with a positive opinion by five workers. The proposed model outperformed existing systems on the supplied dataset. The proposed technique works well on the Flickr dataset and does not require any fine-tuning. GoogleNet surpassed past efforts using AlexNet by more than 9%. Transforming GoogleLeNet into a framework for visual sentiment analysis led to improved feature extraction. Hyper settings ensured a steady and long-lasting state.

The authors [26] introduced deep learning for sentiment analysis on Twitter. Their approach focused on initializing the variable value in a convolutional neural network, ensuring precise training without requiring new features. The word embedding is created with a neural language and trained on a huge unsupervised dataset of tweets. On large supervised datasets, traditional neural networks are utilized to improve embedding. The network was trained using pre-implemented words and parameters, using the same supervised corpus and architecture as Semeval 2015. The suggested method makes use of convolutional layer structure, softmax, activations, and word matrix pooling. The network was constructed using non-convex optimization techniques and stochastic gradient descent (SGD). The backpropagation method was used to compute gradients, and dropout techniques were used to enhance the regularization of neural networks. The (DL) model correctly predicts polarity on two Semeval-2015 problems at the message and phrase levels. Using six test sets, the recommended model had the highest accuracy.

Conducted extensive study [27] on sentiment analysis in micro-blogs. The objective was to gather user feedback on trending events using a Convolutional Neural Network (CNN). CNN uses training data to learn intuitively, eliminating the need for explicit feature extraction. The study employed a targeted crawler to collect data from 1000 micro-blog comments, which were categorized as neutral, negative, or favorable. The proposed model was compared to previous studies that used CRF, SVM, and other standard sentiment analysis approaches. The price is steep. The proposed technique significantly enhances emotion analysis accuracy, as evidenced by its performance. Investigated how to [28] regulate social multimedia content using linguistic and visual sentiment analysis technologies. The sentiment analysis of images and text was assessed using CNN and paragraph vector models, respectively. The proposed model is called the rule-based sentiment classifier VADER. Integrating both visual and textual elements fared better than sentiment analysis techniques that just used visual data, according to studies conducted with both manually classified and poorly classified visual tweets. The study demonstrated how models could be easily transferred between domains using tools such as Getty Images, Caffe, Twitter API, Crowd intelligence or Mechanical Turk. Based on findings, the hybrid textual-visual model scored better than approaches that only used textual or graphical sentiment analysis instead.

The scholar [15] suggested a seven-layer system for assessing phrase emotions. This framework uses CNNs (Convolutional Neural Networks). Word2vec is used to compute SA and vector representation, respectively. Google suggested Word2vec. The Parameter Rectified Linear Unit (PReLU), standardization, and withdrawal technologies were employed to increase both the precision and the generality of the suggested model. The technique was tested using movie review excerpts from rottentomatoes.com. Five labels are present in the dataset: neutral, negative, somewhat negative, positive, and slightly positive. The proposed method outperformed previous method, such as (MV RNN) and RNN, achieving an accuracy of 45.5%. Table 1 provides a summary of the top experiments utilizing the CNN.

2.2 Recursive Neural Network (RNN)

Supervised learning involves the application of RNNs (recursive neural networks) [24]. Nodes may have unique matrices, and the tree topology is predetermined prior to training. RNN minimizes the need for input reconstruction. The absence of labeled, sizable corpora in present method is addressed by the proposed work [29], which constructs a

Treebank for Chinese sentiments in social information. When predicting whether words were beneficial or detrimental, the recursive neural deep model fared better than SVM, Naive Bayes, and Highest Entropy. We gathered 2,270 movie reviews from the internet and used the Chinese word segmentation tool ICTCLAS to process them. Sentences were separated into five classes and processed with the Standford parser. The proposed method improves emotion label prediction for 13,550 Chinese phrases and 14,964 words. ME and NB significantly outperform the baselines, especially when handling contrastive conjunction structures.

This study [30] presents a model that precisely captures compositional effects at various phrase levels by utilizing the emotion treebank and recursive neural tensor network, including both favorable and unfavorable terms. The proposed method was evaluated against all existing method. Existing method cannot sufficiently represent the meaning of extended sentences in semantic word spaces. As a result, sentiment identification needs additional supervised evaluation and training resources, as well as The RNTN achieved a sentiment prediction accuracy of 80.7% with fine-grained labeling for all words, surpassing the performance of previous influential composition models. This study [31] presents a comprehensive and scalable approach for identifying top carding/malware providers. According to user reviews, the method uses thread categorization, snowball sampling, and (DL) for (SA) to evaluate a seller's performance in terms of goods or services. The proposed method was evaluated on a Russian carding forum, where discussion information was collected using a web crawler. A sentiment treebank was developed using a recursive neural network and a collection of online reviews. Two tests were conducted to assess the suggested model's validity and efficacy when compared to NaveBayes, KNN, and SVM-based models. This study identifies stores with high fraudulent ratings and evaluates the effectiveness of deep learning in detecting them. Deep learning methods outperform shallow classifiers and card merchants receive lower ratings compared to virus vendors. **Table 1** explores the best strategies for using recursive neural networks.

2.3 Deep Neural Networks (DNN)

A sentiment analysis technique that integrates textual and visual data from social networks is presented in this investigation [32]. This approach employs (DNN) techniques like Skipgram and Enhancing Autoencoders and is based on the continuous Bag-of-Words (CBOW) design. The two components of the suggested approaches for textual content are CBOW-DA-LR and CBOW-LR (logistic regression). Sentiment is classified by the polarity of both written and visual information. The model was tested on four datasets: Sentiment 140, SentiBank Twitter, SemEval 2013, and Sanders Corpus. The suggested approach outperforms the fully supervised probabilistic language model FSLM as well as CBOW+SVM. An extended fully supervised probabilistic language model is called an ESLAM could have potentially yielded better results with shorter training data. To achieve the best performance, both feature learning and skipgram techniques require large datasets. This analysis [33] proposes a deep neural network architecture for evaluating document similarity. The model was tested using market news to generate vectors for news stories. T&C News served as the information. The labeled articles were compared using cosine similarity, and the document polarity was considered, but not the contents. The recommended approach performed better in evaluating article similarity based on polarity. **Table 1** presents the results of two methods that use (DNN).

2.4 Recurrent Neural Networks (RNN)

A popular technique for language modeling is the (RNN) [24], which does not rely on fixed-length sentences that could skew the context. A hierarchical bidirectional recurrent neural network (HBRNN) was used in this analysis [34] to gather brief client feedback for different hotels. HBRNN employs RNN language to represent consecutive long-term data and provides review-level predictions. Data used in the experiment came from the 2015 DBS Text Mining Challenge. By optimizing the network metrics, HBRNN outperformed (LSTM) and BLSTM (Bidirectional LSTM) in terms of performance. The studies employed substantially skewed data to assess memory, F1 scores, and accuracy. To evaluate HBRNN performance with benchmark systems, we used development, test set, and train splits, as well as tenfold cross validation. The primary challenges addressed are the lack of high-quality online reviews and the imbalance in the analyzed data. According to the experimental findings, HBRNN performed better than alternative techniques on the dataset. This technique could be applied to large-scale opinion mining projects. This contribution [35] tackles the challenge of utilizing a standardized and extensive Bangla dataset for Sentiment Analysis. A sizable dataset of 10,000 Bangla and Romanized Bangla texts has been made available for sentiment analysis in order to address the problem. The dataset was analyzed using a Deep Recurrent method, specifically LSTM, as well as binary and categorical cross-entropy loss functions. Information was gathered from a number of websites, such as Facebook, Twitter, and YouTube. The experiments entailed creating a dataset and comparing one mark to another to determine if it resulted in better outcomes.

A sequence approach for embedding product reviews across time was developed by the author [36], which had received little attention in earlier studies. We train distributed embeddings of clients and items using a combination of recurrent neural networks and gated recurrent units. These emotion embeddings were employed to build a machine learning algorithm. Three datasets from IMDB and Yelp were used to test the approach. The rating level is used to tag each review. The Adam stochastic optimization approach and the back-propagation algorithm were used to develop the network. Sentiment categorization at the file level is improved by sequence modeling for distributed representations of individuals and products. On benchmark datasets, the proposed approach produces sophisticated results. The suggested model was contrasted with a number of baselines, including the JMARS method, word2vec, user-product neural networks, recursive neural networks, and paragraph vectors. Various methods using Recurrent Neural Networks were explored, as demonstrated in **Table 1**.

2.5 Deep Belief Networks (DBN)

Deep belief networks (DBNs) [37] consist of multiple hidden layers made up of restricted Boltzmann machines (RBMs). DBNs have been shown to be an efficient method for feature illustration. Unlabeled information is used to address problems involving labeled analysis. This paper [38] introduces WSDNNs, an innovative deep neural network architecture. WSDNNs allow sentiment labels to be exchanged across both languages. At various low-frequency levels, both cross-linguistic and language specific features were displayed. The Prettenhofer and Stein databases were accessed in four languages: French, German, English, and Japanese. During cross-lingual information transfer, the feature spaces of the source and destination languages should overlap as little as possible, the article suggests adopting backpropagation, which outperforms earlier work. DNNs translate information between source and destination languages. Experiments were conducted to assess sentiment in Amazon product reviews in many languages. The proposed method outperformed previous cross-lingual sentiment classification trials.

Another study [17] used word vectors and a deep belief network to identify political content in Korean newspapers. The suggested model makes use of word2vec, KKMA for morpheme analysis, a Python web crawler to collect news items, a five-step pipeline to detect political bias, SVM for bias calculation, and the scikit-learn package. Between January 1, 2014, and February 28, 2015, 50,000 political articles were included in the dataset. With a mean square error of 0.12, the findings showed an accuracy of 81.8\% in accurately identifying labels. In this analysis [37], To solve vocabulary issues, a deep belief network with feature selection (DBNFS) was implemented. A collection of hidden layers in an input corpus was also used by the network. By removing duplicate characteristics and standardizing vocabulary data, the Chi-Squared feature selection strategy improved the Deep Belief Network (DBN). The DBN learning phase was enhanced to DBNFS using the Chi-Squared method. This research involved several classification tasks, including data partitioning, feature selection, model training, and evaluation, as well as two novel ones: feature selection and reduction. The recommended DBNFS method was compared to existing algorithms in terms of performance, training length, and accuracy. Using datasets such as books (BOO), electronics (ELE), DVDs (DVD), kitchen appliances (KIT), and movie reviews (MOV), five sentiment categories were evaluated. The learning settings were maintained in line with earlier research to provide a fair comparison. By comparing the number of characteristics pri or to and during selection and reduction, accuracy was determined. When compared to previous efforts, the accuracy results revealed that DBNFS exceeded DBN. DBNFS requires shorter training time than DBN. The recommended feature selection technique and streamlined deep structure resulted in quicker training times. The only disadvantage of DBN is its high cost and time-consuming requirements. **Table 1** provides an overview of DBN-based sentiment analysis methods.

2.6 Hybrid Neural Networks

(LSTM) and (CNN) are two deep learning algorithms for sentiment categorization that are described in this study [8] using Thai Twitter data. The data processing was completed successfully. Thai Twitter users and their followers provided the information. Data was filtered to contain just Thai-language tweets and characters. Five tests to improve deep learning parameters were carried out. contrast them with conventional methods, and determine the value of word sequences. The method was validated using threefold cross validation. According to the study, DNN outperforms LSTM in terms of accuracy, and that (DL) algorithms surpass SVM and Naive Bayes but fall short of Maximum Entropy. Original sentences demonstrated greater accuracy than scrambled ones, emphasizing the importance of word order.

A hybrid model combining a two-layered Restricted Boltzmann (RBM) and Probabilistic Neural Network (PNN) is presented in this research paper [39]. The recommended hybrid deep learning structure is designed to increase sentiment classification accuracy. This technique succeeds at recognizing negative and positive reviews based on context, but it does not consider neutral evaluations. Experiments were carried out using datasets from several researchers with binary classification performed on each dataset. The result of five datasets has increased when compared to authors cutting-edge model [13]. The proposed approach is faster than rivals since it does not require external resources such as POS taggers or sentiment dictionaries. To reduce the number of features, dimensionality reduction was conducted. Previous research used a complex approach for feature selection. **Table 1** covers ways that employ hybrid neural networks.

2.7 Other Neural Networks

To address the complexities of word-level models, this research [40] suggests a character-based approach. The proposed CDBLSTM model builds on the current DBLSTM neural network model [41]. This study categorizes tweets as either good or negative by examining textual content and tweet polarity. Only positive and negative data are included in the model categories for comparison with existing data, though other classifications, such as neutral or more granular distinctions, could be considered. Character-level encoding and training are applied to tweets using categorical cross-entropy (CCE). Two datasets were employed for the experiments: the GO dataset and the latest benchmark dataset for SemEval 2016. Every model was trained to utilize the Adam optimizer with a 0.1 learning rate. A logistic regression model was used to make the final predictions. The outcomes show that the suggested approach works well for problems involving polarity categorization. Experiments show that CDBLSTM beats DBLSTM and is comparable to Deep Convolutional Neural Network (DCNN) [42] in sentiment polarity classification on Twitter. The accuracy of SemEval-2016 was 84.82\%, but the accuracy of the STS (Stanford Twitter Sentiment) corpus was 85.86\%. The study [41] recommends classifying sentiment in Hinglish text using TF-IDF, GR, and RBFNN. While sentiment analysis has been studied in a number of languages, including Arabic, Chinese, English, Turkish, Flemish, and Spanish, it has not been studied in Indic languages.

Hinglish, a combination of Hindi and English, was used to categorize sentiments in order to close this gap. Content from news articles and Facebook comments is included in the dataset. Keep track of Term Matrix and Inverse Term Frequency Five feature selection techniques—information gain, chi-square, t-statistics, association, and gain ratio—were used to examine document frequency. Random forest, naive bayes, logistic regression, CART, decision trees, support vector machines, and radial basis function neural networks, and multilayer perceptron were among the classifiers used for data classification. The datasets underwent 840 tests in all, and the best outcomes were found. The suggested triad method worked quite well for classifying sentiment in Hinglish text.

The difficulty of precisely assessing customer perceptions of businesses in the blogosphere is discussed in this article [42]. Utilizing the benefits of (Ml) and semantic orientation indexing, the study suggests a neural network (NN)-based method for effectively categorizing feelings. The neural network's input is semantic orientation indexes. Due to its error tolerance, the proposed approach makes use of a back-propagation neural network (BPN) as its primary learner. Data was collected from real-world blogs, including "LiveJournal" and "Review Center." We performed word segmentation, sentiment orientation (SO) index calculation, neural network training, and performance assessment. The training and testing datasets were predefined. Metrics such as The F1 score, assessment matrices, and overall precision were utilized for performance measurement. In comparison to existing ML and IR techniques, the proposed strategy increased classification performance while reducing training time.

A data-driven supervised approach to feature reduction and vocabulary development for brand sentiment analysis on Twitter was presented in this paper [43]. For feature reduction and Twitter-specific vocabulary development, statistical analysis and n-grams were utilized. SVM and Naive Bayes methods were employed for the Twitter-focused vocabulary in order to compare it to previous studies. The suggested approach beat earlier algorithms by classifying Twitter-specific phrases using artificial neural networks. To increase accuracy, Training and testing sets were created from the datasets, and the input data was represented as a parse matrix. During the feature engineering phase, preprocessing processes were performed to streamline documents and generate vector presentations. TwitterAPI v1.0 was used to gather the data. Compared to earlier studies, the suggested approach showed that emotions had a greater explanatory value when used on Justin Bieber's Twitter dataset. The suggested method increases classification accuracy and coverage by removing attributes from the Justin Bieber corpus. Out of 181 terms, just six were related to Justin Bieber's brand, with the rest being Twitter-specific. The recommended process assisted Justin Bieber in identifying brand challenges and points of view.

Table 1. Comparing Machine Learning with Ensemble Learning Techniques.

Author Name and Year	**Model Name**	**Objective**	**Data Set**	**Result**
J Islam and Y Zhang2016 [25]	CNN.	VisualS	1269 images fromtwitter	GoogleNet outperformed AlexNet by nearly 9% in performance.
A Severyn and A Moschitti 2015 [26]	CNN.	Phrase-level and message-level taskSA	Semeval2015.	Comparing it against the official system, it ranked second in the message-level task and first in the phrase-level subtask.
L Yanmei and C Yuda 2015 [27]	CNN.	Sentiment analysis for microblog data	1000 comments from microblogs (Hua-Qiangu dataset)	improved accuracy in identifying emotional orientations.
Q You, J Luo, H Jin, and J Yang, 2015 [28]	CNN.	(Textual-visual(SA))	Getty-Images, 101keywords	Compared to earlier solo fusion methods, an integrated textual and visual model performs better.
X Ouyang, P Zhou, C H Li, and L Liu, 2015 [15]	CNN.	Phrase sentiment analysis	Movie review snippets	Achieved 43% accuracy, surpassing previous approaches.
C Baecchi, T Uricchio, M Bertini, and A Del Bimbo, 2016 [32]	CBOW DA-LR.	(Visual and Textual (SA))	SandersCorpus, Sentiment14, SemEval2013 and Senti-Bank Twitter Dataset	Displayed superior classification accuracy compared to earlier methods.
H Yanagimoto, M Shimada, and A Yoshimura, 2013 [33]	DNN.	Estimating the similarity between documents	(T&C)News	Enhanced performance in estimating article similarity based on polarity.
R Silhavy, R Senkerik, Z K Oplatkova, P Silhavy, and Z Prokopova, 2016 [34]	HBRNN.	Analysis of Customer Reviews' Sentiment	150,175Labelled reviews from 1500hotels (DBS text-mining-Challenge2015)	The test findings showed that (HBRNN) worked better than any other technique.
A Hassan, M R Amin, A	LSTM.	SA-on Bangla and Romanized Bangla	Posts from various social media platforms	Reduced ambiguity with an accuracy of 78%; ambiguous cases converted to a score of 2

Kalam, A Azad, and N Mo-hammed, [35]		Text		attained a highest accuracy of 55%.
T Chen, R Xu, Y He, Y Xia, and X Wang , 2016 [36]	RNN-GRU	Acquiring Knowledge about User and Product Distribu-tion Representa-tions	Three-datasets collected from (Yelp and IMDB) .	The findings show that the suggested model performed better than a number of baselines, including as the (JMARS) algorithm, word2Vec, user product neural net-works, recursive neural networks, and paragraph vectors.
G Zhou, Z Zeng, J X Huang, and T He, 2016 [38]	WSDNN s.	Multilin-gual Sentiment Categoriza-tion	(Four-languages reviews from amazon)	The suggested method was evaluated on 18 cross-lingual sentiment cate-gorization tasks, and it proved to be more potent and successful than earlier research.
T Mikolov, K Chen, G Cor-rado, and J Dean, 2013 [17]	DBN + Word Vectors	Identifying politics in Korean texts	50,000 political articles	Achieved an 82% accuracy rate in predicting labels.
P Ruangka-nokmas, T Acha-lakul, and K Akkarajitsa-kul, 2016 [37]	DBNFS.	Feature Se-lection	Five datasets, including movie reviews and multidomain da-tasets (2000 reviews: 1000 positive, 1000 negative)	The precision outcomes were contrasted with those from earlier research, demonstrating that DBNFS outperforms DBN.
P Vateekul and T Koomsubha , 2016 [8]	CNN - LSTM.	SA on Thai-Twit-ter Data	(3,813,173-tweets), (33,349-nega-tivetweets and 140,414 positive tweets)	It outperforms SVM and Na-ive Bayes in accuracy but falls short of Maximum Entropy. The accuracy is higher for original sentences compared to shuffled sen-tences.
R Ghosh, K Ravi, and V Ravi, 2016 [39]	PNN + RBM	Improved sentiment classifica-tion accuracy	Pang, Lee, and Blitzer datasets (1000 positive, 1000 negative reviews for DVDs,	Accuracy: Movies = 92%, Books = 93%, DVDs = 93%, Electronics = 93%, Kitchen Appliances = 95%.

			books, kitchen appliances, electronics)	
R Goebel and W Wahlster, 2011 [40]	DBLSTM.	SA of Social-Data	(Sem-Eval-2016) and Go-dataset (1.6 million-tweets)	Precision: 85.86% on Stanford Twitter Sentiment sample, 85% on SemEval-2016
K Ravi and V Ravi, 2016 [41]	RBFNN.	Classification of sentiment in Hinglish writing	(300-news articles from VizNews and Facebook).	The suggested method scored well. in terms of sensitivity than specificity using the news dataset. The suggested method outperformed sensitivity in terms of specificity using the Facebook information.
L S Chen, C H Liu, and H J Chiu, 2011 [42]	BPN.	Sentiment classification in the Blogging sphere	Reviews have been collected using Live-Journal and Review Center.	Comparing the suggested approach to conventional ML and IR techniques, the findings showed that it decreases training time and enhances classification performance.
M Ghiassi, J Skin ner, and D Zimbra, 2013[43]	DANN	Twitter sentiment analysis (Justin Bieber brand)	Total-10,345,184 tweets related to (Justin Bieber) brand	According to the findings, 97% of the (10,345,184 tweets in the Justin Bieber sample were caught by a reduced feature set), however more than 80.1% of tweets lacked emotion. Just six of the 181 phrases had anything to do with the Justin Bieber brand, which helped pinpoint the problems and viewpoints around it.

3 Analysis

This review highlights sentiment analysis research employing deep learning models, as illustrated in Table 1. Deep learning algorithms can increase sentiment analysis efficiency and accuracy, according to a comprehensive examination of all research. Deep learning models, which mimic the human brain, beat shallow models in predicting user attitudes. Deep learning networks surpass SVMs and traditional neural networks due to their multiple hidden layers, whereas conventional neural networks typically contain just one or two levels that are concealed. Both controlled and unsupervised training environments are possible for these networks. Deep learning algorithms extract features automatically without the need for human involvement, which saves time by removing the need for feature engineering. Sentiment analysis involves a variety of problem statements. The system's capacity to adapt to task changes with little adjustments improves its overall safety and strength. The Deep Learning benchmark comes with certain limitations compared to earlier models like SVM. Training on extensive datasets is resource-intensive and costly. Complex models can require weeks to train, even on high-end GPU-powered systems.

4 Conclusion

Sentiment analysis focuses on understanding emotions, opinions, and subjective text. The growing need to evaluate and organize data has raised the need for sentiment analysis. Hidden insights are extracted from social media using unstructured data. Deep learning has become a key tool for implementing sentiment analysis, as its models are effective and widely applied to address various challenges. This article reviews several studies that highlight the efficacy of DL applications SA. The high accuracy achieved through sentiment analysis and deep learning has contributed significantly to solving numerous challenges.

References

1. A. V. Yeole, P. V. Chavan, andM. C. Nikose, Opinionmining for emotions determination, ICIIECS2015 IEEE Int. Conf. Innov. Information, Embed. Commun.Syst.,2015.
2. JB. Heredia, T. M. Khoshgoftaar, J. Prusa, and M. Crawford, Cross Domain Sentiment Analysis: An Empirical Investigation, 2016 IEEE 17th Int. Conf. Inf. Reuse Integr., pp. 160165.
3. F. Luo, C. Li, and Z. Cao, Affective-feature-based sentiment analysis using SVM classifier, 2016 IEEE 20th Int. Conf. Comput. Support. Coop. Work Des., pp. 276281.
4. M. Haenlein and A. M. Kaplan, An empirical analysis of attitudinal and behavioral reactions toward the abandonment of unprofitable customer relationships, J. Relatsh. Mark., vol. 9, no. 4, pp. 200228, 2010.
5. J. Singh, G. Singh, and R. Singh, A review of sentiment analysis techniques for opinionated web text, CSI Trans. ICT, 2016.
6. E. Aydogan and M. A. Akcayol, A comprehensive survey for sentiment analysis tasks using machine learning techniques, 2016 Int. Symp. Innov. Intell. Syst. Appl., pp. 17.
7. M. Day and C. Lee, Deep Learning for Financial Sentiment Analysis on Finance News Providers, no. 1, pp. 11271134, 2016.
8. P. Vateekul and T. Koomsubha, A Study of Sentiment Analysis Using Deep Learning Techniques on Thai Twitter Data, 2016.
9. Y. Zhang, M. J. Er, N. Wang, M. Pratama, and R. Venkatesan, Sentiment Classification Using Comprehensive Attention Recurrent Models, pp. 15621569, 2016.
10. S. Zhou, Q. Chen, and X. Wang, Active deep learning method for semi-supervised sentiment classification, Neurocomputing, vol. 120, pp. 536546, 2013.
11. L. Deng, G. Hinton, and B. Kingsbury, New types of deep neural network learning for speech recognition and related applications: an overview, 2013 IEEE Int. Conf. Acoust. Speech Signal Process., pp. 85998603.

12. S. Bengio, L. Deng, H. Larochelle, H. Lee, and R. Salakhutdinov, Guest Editors Introduction: Special Section on Learning Deep Architectures, IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 8, pp. 17951797, 2013.
13. L. Arnold, S. Rebecchi, S. Chevallier, and H. Paugam-Moisy, An Introduction to Deep Learning, Esann, no. April, p. 12, 2011.
14. Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, Deep learning for visual understanding: A review, Neurocomputing, vol. 187, pp. 2748, 2016.
15. X. Ouyang, P. Zhou, C. H. Li, and L. Liu, Sentiment Analysis Using Convolutional Neural Network, Comput. Inf. Technol. Ubiquitous Com put. Commun. Dependable, Auton. Secur. Comput. Pervasive Intell. Com put. (CIT/IUCC/DASC/PICOM), 2015 IEEE Int. Conf., pp. 23592364.
16. R. Socher and C. Lin, Parsing natural scenes and natural language with recursive neural networks, Proc. , pp. 129136, 2011.
17. T. Mikolov, K. Chen, G. Corrado, and J. Dean, Efficient Estimation of Word Representations in Vector Space, Arxiv, no. 9, pp. 112, 2013.
18. N. Kalchbrenner, E. Grefenstette, and P. Blunsom, A Convolutional Neural Network for Modelling Sentences, Acl, pp. 655665, 2014.
19. Y. Kim, Convolutional Neural Networks for Sentence Classification, Proc. 2014 Conf. Empir. Methods Nat. Lang. Process. (EMNLP 2014), pp. 17461751.
20. T. Mikolov, K. Chen, G. Corrado, and J. Dean, Distributed Represen tations of Words and Phrases and their Compositionality, Nips, pp. 19, 2013.
21. Z. Wu, T. Virtanen, T. Kinnunen, E. S. Chng, and H. Li, Exemplar-based unit selection for voice conversion utilizing temporal Information, Proc. Annu. Conf. Int. Speech Commun. Assoc. INTERSPEECH, pp. 30573061, 2013.
22. K. S. Tai, R. Socher, and C. D. Manning, Improved semantic repre sentations from tree-structured long short-term memory networks, Proc. ACL, pp. 15561566, 2015.
23. A. A. Al Sallab, R. Baly, and H. Hajj, Deep Learning Models for Sentiment Analysis in Arabic, no. November. 2015.
24. C. Z. Jiajun Zhang, Neural Networks in Machine Translation: An Overview, IEEE Intell. Syst., pp. 17241734, 2015.
25. J. Islam and Y. Zhang, Visual Sentiment Analysis for Social Images Using Transfer Learning Approach, 2016 IEEE Int. Conf. Big Data Cloud Comput. (BDCloud), Soc. Comput. Netw. (SocialCom), Sustain. Comput. Commun., pp. 124130.
26. A. Severyn and A. Moschitti, Twitter Sentiment Analysis with Deep Convolutional Neural Networks, Proc. 38th Int. ACM SIGIR Conf. Res. Dev. Inf. Retr.- SIGIR 15, pp. 959962, 2015.
27. L. Yanmei and C. Yuda, Research on Chinese Micro-Blog Sentiment Analysis Based on Deep Learning, 2015 8th Int. Symp. Comput. Intell. Des., pp. 358361.
28. Q. You, J. Luo, H. Jin, and J. Yang, Joint Visual-Textual Sentiment Analysis with Deep Neural Networks, Acm Mm, pp. 10711074, 2015.
29. C. Li, B. Xu, G. Wu, S. He, G. Tian, and H. Hao, Recursive deep learn ing for sentiment analysis over social data, Proc.- 2014 IEEE/WIC/ACM Int. Jt. Conf. Web Intell. Intell. Agent Technol.- Work. WI IAT 2014, vol. 2, pp. 13881429.
30. R. Socher, A. Perelygin, and J. Wu, Recursive deep models for semantic compositionality over a sentiment treebank, Proc. , pp. 16311642, 2013.
31. W. Li and H. Chen, Identifying top sellers in underground economy using deep learning-based sentiment analysis, Proc.- 2014 IEEE Jt. Intell. Secur. Informatics Conf. JISIC 2014, pp. 6467.

32. C. Baecchi, T. Uricchio, M. Bertini, and A. Del Bimbo, A multimodal feature learning approach for sentiment analysis of social network multi media, Multimed. Tools Appl., vol. 75, no. 5, pp. 25072525, 2016.
33. H. Yanagimoto, M. Shimada, and A. Yoshimura, Document similarity estimation for sentiment analysis using neural network, 2013 IEEE/ACIS 12th Int. Conf. Comput. Inf. Sci., pp. 105110.
34. R. Silhavy, R. Senkerik, Z. K. Oplatkova, P. Silhavy, and Z. Prokopova, Artificial intelligence perspectives in intelligent systems: Proceedings of the 5th computer science on-line conference 2016 (CSOC2016), vol 1, Adv. Intell. Syst. Comput., vol. 464, pp. 249261.
35. A. Hassan, M. R. Amin, A. Kalam, A. Azad, and N. Mohammed, Bangla Text (BRBT) using Deep Recurrent models.
36. T. Chen, R. Xu, Y. He, Y. Xia, and X. Wang, Using a Sequence Model for Sentiment Analysis, no. August, pp. 3444, 2016.
37. P. Ruangkanokmas, T. Achalakul, and K. Akkarajitsakul, Deep Belief Networks with Feature Selection for Sentiment Classification, Uksim.Info, pp. 16, 2016.
38. G. Zhou, Z. Zeng, J. X. Huang, and T. He, Transfer Learning for Cross-Lingual Sentiment Classification with Weakly Shared Deep Neural Networks, Proc. 39th Int. ACM SIGIR Conf. Res. Dev. Inf. Retr.- SIGIR 16, pp. 245254, 2016.
39. R. Ghosh, K. Ravi, and V. Ravi, A novel deep learning architecture for sentiment classification, 3rd IEEE Int. Conf. Recent Adv. Inf. Technol., pp. 511516, 2016.
40. R. Goebel and W. Wahlster, Integrated Uncertainty in Knowledge Modelling and Decision Making, Proc. Int. Symp. Integr. Uncertain. Knowl. Model. Decis. Mak. (IUKM 2011), vol. 1, pp. 362373, 2011.
41. A. Graves, N. Jaitly, and A. R. Mohamed, Hybrid speech recognition with Deep Bidirectional LSTM, 2013 IEEE Work. Autom. Speech Recog nit. Understanding, ASRU 2013-Proc., pp. 273278.
42. C. N. dos Santos and M. Gatti, Deep Convolutional Neural Networks for Sentiment Analysis of Short Texts, Coling-2014, pp. 6978.
43. K. Ravi and V. Ravi, Sentiment classification of Hinglish text, 2016 3rd Int. Conf. Recent Adv. Inf. Technol. RAIT 2016, pp. 641645.