Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7778511

E-COMMERCE USER PRODUCT RATING ANALYSIS: A REVIEW OF DEEP LEARNING MODELS

Krishan Kumar[1*], Dr.Randeep Singh[2]
[1*]Reseacrh scholar Department of Computer science & Engineering, IEC University Baddi Solan (HP), India, E-mail: krishan.pingle@gmail.com
[2]Professor Department of computer science & Engineering, IEC University Baddi, Solan (HP), India, E-mail: randeeppoonia@gmail.com

***Corresponding Author:** Krishan Kumar
*Reseacrh scholar Department of Computer science & Engineering, IEC University Baddi Solan (HP), India, E-mail: krishan.pingle@gmail.com

Abstract. The discipline of sentiment classification has gained prominence in the domain of Natural Language Processing (NLP) due to its focus on identifying the overall sentiment conveyed in a given text. Significantly, deep learning models have shown exceptional effectiveness in this particular field. User feedback is of utmost importance in improving the efficacy of recommender systems, since it often encompasses a wide range of emotional data that has the ability to influence the accuracy and precision of suggestions. The information given by users is subjected to analysis using a deep learning model to provide a potential user rating, which may afterwards be used for the purpose of making recommendations. The essay starts by offering a thorough delineation of emotion analysis and expounding upon its many applications. The ensuing discourse centred on the use of recurrent neural networks (RNNs), long short-term memory (LSTM) networks, deep belief networks (DBNs), and hierarchical deep belief networks (HDBNs) within the framework of sentiment analysis.
Keywords: Sentiment Analysis; RNN; LSTM; HBDN; DBN;

1. Introduction

The analysis of implicit user sentiment has significant significance in the domains of recommender systems and customization, since it enables the detection of users' sentiments towards a service, even when clear verbal expressions are not provided. Alternative methodologies, such as result similarity-based methods, might be used to achieve the given target instead of relying only on machine learning techniques [1]. The data used for sentiment analysis (SA) is obtained from social media platforms, where individuals regularly generate and distribute content. Hence, it is essential that the process of integrating "big data" include a diverse array of data sources. The need of addressing additional issues arises from the need to assure the effective storage, retrieval, and analysis of data, while simultaneously guaranteeing the accuracy of outcomes [2].

There is an increasing emphasis on the field of automated sentiment analysis (SA). The undertaking of sentiment analysis (SA) is essentially intricate and encounters several hurdles within the realm of natural language processing (NLP), notwithstanding its significant significance and extensive array of present applications. Ongoing academic research in the field of sentiment analysis consistently faces several theoretical and technological challenges, which complicate the process of determining an individual's position in an argument, resulting in a complex undertaking [3,4]. The study done by Hussein et al. [4] aimed to examine the impact of sentiment structure on accuracy. The aforementioned findings provide empirical evidence to support the importance of accuracy in contemporary research on sentiment analysis. Furthermore, the system has inherent limitations, such as difficulties in accurately interpreting negation and its reliance on certain domains.

A considerable proportion of news organisations in South Africa have shifted their principal mode of distribution to social media platforms. The increasing prevalence of social networks is significantly impacting the enhancement of connection and complexity inside data networks.

In contemporary times, there has been a noticeable increase in the number of concepts related to sentiment analysis that heavily depend on deep learning approaches. There are variations in the capacity and calibre of the evaluations. This article offers a comprehensive study of recent academic endeavours that have used deep learning methodologies, namely deep neural networks (DNN), recurrent neural networks (RNN), and convolutional neural networks (CNN), to investigate many facets of sentiment analysis. These questions include the examination of sentiment polarity and aspect-based sentiment. Cutting-edge deep learning techniques were used for sentiment analysis, including sophisticated approaches like TF-IDF and word embeddings seamlessly integrated into deep learning frameworks. The aforementioned methodologies were especially used in the examination of datasets obtained from the Twitter network.

1.1. Word Embedding

Within the domain of natural language processing (NLP), a considerable proportion of deep learning models rely extensively on the method of feature extraction, namely from word embeddings [5]. The use of word embeddings may serve the objective of language modelling and provide a more profound comprehension of its intrinsic characteristics. The methodology entails the transformation of lexical phrases into vector representations characterised by certain number values. As an example, the concept of a "hat" is transformed into a vector representation comprising of continuous real numbers (..., 0.15, 0.23, 0.41). The procedure often utilises a mathematical conversion that transforms a high-dimensional sparse vector space, such as a vector space encoded using the one-hot encoding technique where each word corresponds to a dimension, into a low-dimensional dense vector space. The vector space dimensions include the encoded characteristics of words. Vectors have the capacity to maintain and exhibit consistencies and patterns inside language.

The enhancement of word structure acquisition may be facilitated by the use of neural networks (6, 9) or matrix factorization (10). The Word2Vec technique has garnered considerable interest due to its high efficacy in word embedding. The suggested methodology entails the use of a prediction model that relies on neural networks to proficiently train word embeddings via the utilisation of textual input. The research employs two models, namely the Skip-Gram (SG) model [8] and the Continuous Bag-of-Words (CBOW) model [7]. The CBOW model utilises contextual information to provide predictions on the semantic meaning of a certain word, such as the term "wearing." The previously described phenomena is seen in the textual excerpt "the boy is wearing a hat," where the underscore sign "_" is used to indicate the specific word being analysed. In contrast, the Skip-Gram approach generates recommendations for neighbouring words only relying on the target word. The CBOW model utilises an approach that involves aggregating the distribution of data by treating the whole context as a single observation. In the context of smaller data sets, it has positive performance features. The SG model has improved performance when faced with bigger datasets, owing to its approach of treating each combination of context and purpose as a distinct observation. Another often used methodology is well recognised is Global Vectors (GloVe) [11]. The training process incorporates the use of a comprehensive word-word co-occurrence matrix that covers entries that are not equal to zero.

2. Literature Review

The primary aim of this research is to provide a theoretical framework that may serve as a guiding principle for future empirical investigations. The aim will be achieved by the investigation and comparison of various techniques and methodologies used in the domain of sentiment analysis. The key elements of the study have been highlighted, including technical difficulties, used datasets, methodologies applied in each inquiry, and potential areas of application.

In recent times, there has been a discernible increase in the use of deep learning models, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), within the field of sentiment analysis, with the objective of augmenting its effectiveness. This article provides a detailed survey of recent improvements in sentiment analysis approaches using deep learning methodology.

Since 2015, a considerable number of researchers have undertaken an inquiry into this particular phenomena. Tang et al. (2012) have developed algorithms using deep learning techniques for the purpose of sentiment analysis. This field encompasses several approaches, including word embedding, sentiment classification, and opinion extraction. The research done by Zhang and Zheng (2013) investigated the use of machine learning methods in the estimation of emotional states. Both study teams used part-of-speech (POS) as a textual attribute and applied term frequency-inverse document frequency (TF-IDF) to evaluate the importance of certain words in their respective investigations. Sharef et al. (2014) conducted an investigation into the possible uses of using large datasets for the purpose of sentiment analysis within the realm of academic discourse. In prior academic literature (references 15-17), researchers have undertaken an investigation and comparative examination of contemporary deep-learning algorithms, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), in the context of sentiment analysis.

Numerous previous research endeavours have used sentiment analysis based on deep learning techniques across various domains, such as economics (18, 19), tweets related to meteorology

(20), online platforms for travel (21), recommendation engines for cloud services (22), and evaluations of films (23). In the research done by [20], the Word2vec programme was used to convert user input and meteorological data into word embeddings. The process included the automatic extraction of textual content from a wide array of data sources. Prior study has used comparable methodologies (24). Jeong et al. (25) developed methodologies aimed at enhancing goods via the use of topic modelling and sentiment analysis findings derived from customer-generated data on social media platforms. The practise of regularly upgrading products has been used as a strategy for doing real-time monitoring in order to examine the evolving preferences of customers. Pham et al. used several knowledge representation approaches to investigate the evaluations conducted by customers about hotels and restaurants in their study. The objective of the research was to determine the viewpoints of consumers about several attributes, including cost, room quality, location convenience, cleanliness, and staff friendliness.

An further methodology (as cited in Reference 26) integrates sentiment and semantic information via the use of a Long Short-Term Memory (LSTM) model, which is specifically designed to identify emotions. In their study, Preethi et al. (2022) used deep learning methodologies to conduct sentiment analysis on the Amazon food dataset. The objective of this research was to develop and deploy a recommender system on a cloud-based platform. In their study, Salas-Zárate et al. (2027) used an approach based on ontology to conduct aspect-level sentiment analysis on tweets related to diabetes in the field of health. The use of deep learning techniques in the examination of tweets for the purpose of ascertaining their polarity is seen in the scholarly investigation cited as reference [28].

The authors provided a thorough explanation of the improvements achieved in the precision of their sentiment analysis via the use of deep learning models. The predominant focus of contemporary models mostly revolves on tweets written in the English language. Nevertheless, considerable efforts have been undertaken to develop models for more languages, such as Spanish [29], Thai [30], and Persian [31].

Prior research has undertaken analysis on tweets using several deep learning models that rely significantly on polarity-based sentiment. Computational models, such as deep neural networks (DNNs), convolutional neural networks (CNNs), and hybrid models, serve as notable examples of phenomena within the discipline. Additional study efforts using neural network models also include an investigation of the intrinsic positive and negative attributes present within textual material throughout their analytical procedures.

In this study, Salas-Zárate et al. (2017) used semantic annotation approaches, with a particular focus on the diabetes ontology, to distinguish and examine various elements. Following this, the researchers performed an aspect-based sentiment analysis using SentiWordNet. In a research done by Pham et al. (2021), customers were questioned to get their viewpoints and evaluations about the importance of certain product qualities. The authors suggest using a layered architecture as a strategy to improve sentiment characteristics and provide a more accurate representation of client evaluations.

The present study included the examination of a comprehensive compilation of 32 academic literature. The findings of this research indicate that prevailing approaches used in the field of sentiment analysis for polarity analysis include deep neural networks (DNNs), convolutional neural networks (CNNs), and hybrid models. The current research examined three diverse approaches in the field of deep learning, namely Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). Every approach underwent rigorous testing using a dedicated dataset. However, it was determined that evaluating the relative merits of the three techniques was not feasible.
The examination of human emotions is an often explored topic within the realm of academic research. During the first phase, textual attributes are automatically collected from a wide array of databases. The text attributes are then transformed into word representations by the use of a software application called Word2vec.

Significant academic endeavours have been devoted to the examination of sentiment analysis within the framework of recommender systems. The field of study utilises several strategies for the process of information filtering, which include content-based filtering, collaborative filtering (CF), demographicbased filtering, and hybrid methodologies. A wide range of methodologies may be used to study data derived from social media platforms, resulting in a varied range of outcomes. Hybrid approaches include the integration of data pertaining to entities and people, which may be obtained or inferred from social media, with data about objects and persons that can be directly collected from the social media platform. This comprises a wide range of data related to different activities, preferences, behaviours, and other important traits.

In addition, recommendation systems are now investigating advanced methodology, such as hybrid approaches and lifelong learning algorithms, in order to efficiently handle explicit data (data directly supplied by users) and implicit data (data inferred from users' actions and behaviours).

The work conducted by Shoham (32) is generally recognised as a significant contribution to the field of hybrid recommendation systems. This recognition arises from the effective incorporation of content filtering and collaborative filtering approaches. The process includes a component focused on content, which entails identifying user profiles by analysing themes derived from internet sources. In contrast, the collaborative filtering component of the system takes into account the evaluations and perspectives of other users inside a certain online platform.

3. Sentiment Analysis

Sentiment analysis is a distinct field of research within the domain of natural language processing (NLP) that focuses on developing computational models with the purpose of detecting and categorising the many emotional nuances inherent in written language. The use of sentiment analysis enables the conversion of unstructured data pertaining to individuals' sentiments towards many issues, including goods, services, brands, politics, and other topics, into organised and significant information. The provided data has the potential to provide important insights for many business applications, including marketing strategies, public relations efforts, product assessments, net promoter score (NPS) analysis, customer feedback analysis, and service improvements.

The sentiment analysis methodology is used to evaluate the polarity of users' input, discerning whether it is positive or negative [33]. The efficacy of sentiment analysis is contingent upon the use of opinion lexicons. Lexical constituents such as "happy," "good," "awful," and "disgusting" exemplify the kind of terms often seen in an opinion lexicon. The inclusion of this particular collection of subjective assertions has significant importance within the realm of sentiment analysis, a scholarly discipline that aims to comprehend individuals' emotional dispositions via their online engagements. In contemporary times, there has been a notable rise in the availability of publicly available lexicons, such as SentiWordNet [34], General Inquirer [35], and SenticNet [36]. The first stage of sentiment analysis involves the identification of opinion targets, including attributes, entities, and issues, which persons are actively discussing [37]. The third stage of the process is the development of a lexicon that encompasses subjective viewpoints. The predominant factor contributing to my level of dissatisfaction may be primarily ascribed to the quality of service provided by this establishment. While the phrase "disappointed" is the intended expression, it is crucial to recognise that the term "disappointing" may also be seen as a subjective assertion.

3.1 Application of Sentiment Analysis

The header is positioned flush with the left margin, without any indentation, and shown in a 17-point Times New Roman Bold font. It is advisable to maintain a top margin of 28 mm and a bottom margin of 10 mm for the title. The potential benefits of sentiment analysis are generally acknowledged in several areas, including the business sector, government realm, and biological field.

The fields of business intelligence and electronic commerce use consumer feedback to improve customer service, boost product quality, and optimise marketing strategies in order to broaden their customer base. The use of sentiment analysis has promise in offering significant insights into the genuine perspectives and perceptions of individuals towards a certain event or object. The research conducted by SA provides valuable insights into customer motives and their responses to market changes. Jain and Dandannavar (2019) introduced a sentiment analysis framework that utilises machine learning methods and Apache Spark to evaluate the sentiment expressed in Twitter datasets with improved efficiency. The system was intentionally designed to possess high speed, flexibility, and the ability to effectively manage huge volumes of data.

In brief, sentiment analysis has played a substantial role in the development of recommender systems. Preethi and colleagues (40) illustrate this assertion via their empirical investigation, whereby they use recursive neural networks to assess the affective responses of readers towards textual reviews. The preceding results were used to train and assess the preferences of a cloud-based recommender system in producing suggestions for eating and leisure options. The use of sentiment research and behavioural analysis has promise in delivering advantages for commodities markets [41].

The field of medicine presents itself as a very auspicious realm for intellectual investigation. The study conducted by [42] examined the use of opinion mining methodologies in health-related social media platforms and blogs. The author proposes using a specialised medical lexicon and novel advancements in machine learning and text processing as a tactic to mitigate the linguistic disparity that currently exists between healthcare practitioners and those seeking medical treatment. The use of sentiment analysis in the field of mental health serves as a supplementary tool or a potential substitute for conventional survey approaches [43]. In the course of this operation, a comprehensive internet inquiry is undertaken to ascertain individuals' social media postings, afterwards followed by an examination of the collected data.

4. Deep Learning Models For Sentiment Analysis

Deep learning may be defined as the use of many layers of artificial neural networks to enhance the process of acquiring knowledge and expertise in various fields (44). The effectiveness of deep learning is widely acknowledged in the domain of machine learning. The technique has the capacity to effectively tackle both supervised and unsupervised learning challenges (Smith, 2010; Johnson, 2012) due to its inherent ability to acquire a wide range of representations and abstractions from input data. Deep learning employs many layers of processing units that function in a non-linear manner to perceive and categorise data. Currently, there is a notable emphasis among researchers on improving sentiment analysis in the domain of natural language processing (NLP).

The task of sentiment analysis may be effectively performed via the use of both supervised and unstructured methodologies. Supervised machine learning encompasses a variety of methodologies, including Support Vector Machines (SVM), Maximum Entropy, Naive Bayes, and other techniques. Unsupervised machine learning encompasses a diverse range of applications, such as the development of emotion dictionaries, grammatical analysis, and the identification of syntactic patterns. The use of deep learning methods in the domain of sentiment analysis has shown a notable increase. Deep learning models are often used in the field of learning tasks because to their remarkable performance and accuracy. The use of deep neural network techniques enables the discernment of unique characteristics within textual material, hence facilitating the efficient classification of succinct phrases.

A. Recurrent Neural Networks

Recurrent neural network (RNN) models, belonging to the neural network family, provide the capability to be used in the examination of natural language. The usage of Recurrent Neural Networks (RNNs) might potentially mitigate challenges associated with limitations imposed by window size. The recurrent neural network has sufficient flexibility to effectively interpret phrases of varying lengths.

The manner in which parameter sharing is handled in recurrent networks demonstrates notable differences compared to other types of networks. The resulting output is influenced to some extent by the preceding element. The same update rule that was used to generate a certain piece of the output was also used to create another segment. The distribution of the parameters of this formula is widespread throughout a computer network of significant complexity due to its broad use [47]. Figure 1 depicts three distinct time phases of the recurrent neural network model.

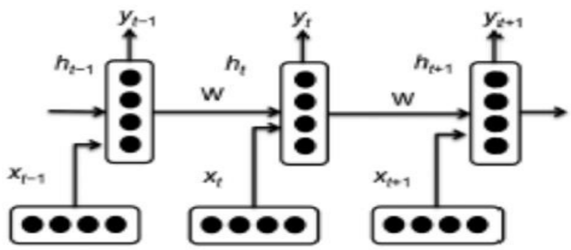

Figure 1: Recurrent Neural Network

B. LSTMs

Long short-term memory networks (LSTMs) are a kind of recurrent neural networks (RNNs) that has the ability to learn information pertaining to long-term dependencies. The architectural configuration of Long Short-Term Memory (LSTM) models has similarities to those of Recurrent Neural Networks (RNNs), but with the noteworthy difference of including supplementary components.

The efficacy of Long Short-Term Memory (LSTM) models relies on the incorporation of the cell state C(t), which is graphically shown as a horizontal line situated in the uppermost part of the diagram. Cell states are an extra kind of information storage, similar to the latent state h(t). However, the enhanced computational skills of Long Short-Term Memory (LSTM) models in handling C(t) processing enable them to efficiently handle far longer sequences compared to traditional Recurrent Neural Networks (RNNs). In addition, Long Short-Term Memory (LSTM) models have the capability to alter the state of a cell via the processes of information deletion or integration. Gates are architectural features used to provide precise control. The effectiveness of information transmission through gates is contingent upon the deliberate purpose of the sender to initiate the procedure. The LSTM cell is fitted with three gates that function to safeguard and regulate its internal state.

The Forget gate is used to selectively eliminate certain components of the prior hidden state h(t-1) by considering the information acquired from the preceding input x(t-1). This facilitates the preservation of just the most crucial information.

A choice has been made to enhance the existing condition, referred to as C, of our cellular structure by integrating the data acquired from the current input, x(t). The element under consideration is often denoted as the input gate (t).

The function of the output gate is to determine the information that will be sent from the current state of the cell (C(t)) to the subsequent state (C(t+1)). Considering the present engagement of the language model with a certain topic, it may be beneficial for the model to proactively predict the likelihood of a verb appearing in the next piece of information. An exemplification may be seen in the incorporation of data on the grammatical number of the subject, which aids in ascertaining the suitable conjugation of the succeeding verb.

Each of these disorders has a correlation with a certain subset of neuronal cells. The intricacy of the implementation procedure for Long Short-Term Memory (LSTM) models is well acknowledged due to these aforementioned issues. Within the present discourse, I will abstain from offering more elucidation about long short-term memory (LSTM) equipment.

In their study, Tang (47) used a considerable quantity of Long Short-Term Memory (LSTM) layers to construct the document model. The sentence vectors that are produced during the first sentence modelling process of the LSTM layer are then used as input for the document-level LSTM. The model demonstrated favourable results when applied to the job of data classification. The Long Short-Term Memory (LSTM) model has received significant recognition for its use in the domain of neural machine translation (NMT). The sequence-to-sequence paradigm is often used by researchers. The architectural architecture of the system integrates Long Short-Term Memory (LSTM) chains, which fulfil the dual functions of serving as both the encoder and decoder components. The sentence is encoded by the encoder, and the decoder employs past predictions to provide an informed estimation for the next word. Zaremba (48) employs a certain methodology in his academic inquiry. In his study, Sutskever (49) provides empirical evidence that demonstrates the possible use of this notion in discerning the correlation between two phrases or recognising sentences that exhibit similarity.

LSTM models have a distinctive capability to incorporate long-term memory into the activation functions inside the hidden layer, distinguishing them from other forms of recurrent neural networks (RNNs). The first proposal of this concept was presented by Hochreiter and Schmidhuber in 1997. Figure 2 depicts the architectural arrangement of the Long Short-Term Memory (LSTM) model. Prior to creating the embedding matrix, the input data undergoes a modification method that has resemblances to the one outlined for the convolutional neural network (CNN). The next layer relates to the Long Short-Term Memory (LSTM) layer. The entity consists of a collection of 200 distinct cellular elements. In the domain of text classification, it is widely acknowledged that the incorporation of a final layer with 128 completely linked cells is a very efficacious approach. The use of the sigmoid activation function in the last layer is employed to convert the 128-dimensional input vector into a single-dimensional output vector. This decision is made based on the need to classify two separate categories within the specified task. (positive, negative).

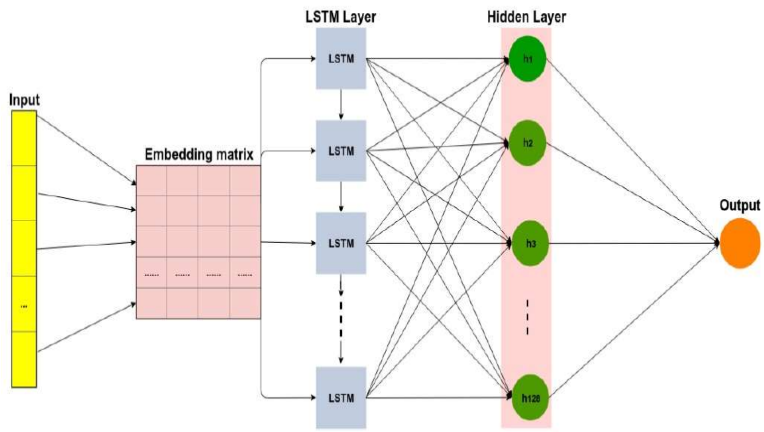

Figure 2: A long short-term memory network

C. Deep Belief Networks (DBN)

The deep belief network (DBN) is an illustrative instance of a generative graphics model characterised by many layers of concealed units interconnected by interlayer connections. An inadequacy in the interconnections is seen among units that belong to the same tier. In the context of Deep Belief Networks (DBN), the first input node is used to determine the most relevant qualities for the input layer throughout the training procedure. The layers inside the system function as detectors of features, and their abilities are obtained from the probabilistic reconstruction of the input, as referenced in [50]. Deep Belief Networks (DBN) may be used to address classification problems [51] via the extrapolation of their training model. The use of Deep Belief Networks (DBNs), as seen in Figure 3, facilitated the production of values that were devoid of particular beliefs and could be stored in terminal nodes. During the first phase, a series of attributes are imparted to enable the precise interpretation of signals acquired from individual pixels. Subsequently, an additional hidden layer is used to extract information pertaining to the attributes of the first hidden layer, whereby the values of the first layer are treated as pixels. By including more characteristics and attributes into a belief network, it is possible to enhance its performance in terms of minimising the logarithmic probability of the training dataset.

After the completion of the training phase, the model is then used on the Test Dataset, which includes both the train and validation sets. In the context of model comparison, it is conventional practise to use the test set. The expected outcomes are not provided, just the objective information is shared. The model's attributes may be estimated and the algorithm's training effectiveness can be evaluated by using testing data. The test dataset is used to objectively evaluate the degree of correspondence between the final model and the training dataset. The text file provided by the user is used as the input for the last stage, which is the prediction phase. The input text file undergoes preliminary, training, and classification operations to ascertain its intended purpose or domain. The inclusion of sentences in a study is contingent upon the research objective or subject matter, as specified in the training dataset. The evaluation of a model's accuracy relies on the extent to which its predictions align with the observed outcomes when the model is applied to test data. The validity of this assertion is evident. Efficiently ascertain the proportion of accurate predictions supplied. To get the average number of tries per correct answer, one may divide the total number of attempts by the ratio of accurate responses.

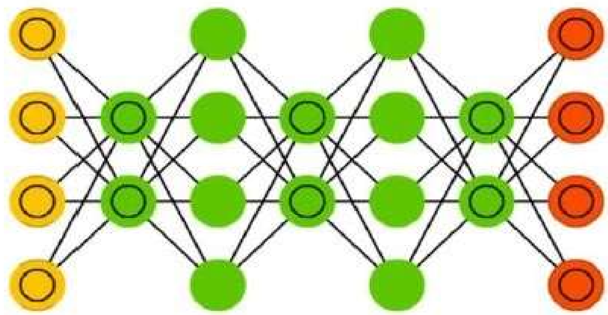

Figure 3: Deep Belief Networks.

D. Hybrid Deep Belief Networks (HDBN)

The HDBN instructional technique is a novel teaching paradigm that obviates the need for ongoing monitoring. Sentiment datasets often display a significant level of complexity, generally including over 10,000 dimensions. To address the computational load associated with convolutional calculations, researchers use Restricted Boltzmann Machines (RBM) as a first approach to reduce the dimensionality of reviews using conventional computations. The complicated structure of HDBN is seen in Figure 4, including several components. The neural network architecture consists of an input layer denoted as h0, a sequence of hidden layers denoted as h1, h2,..., hN, and a label layer referred to as label. The subject being assessed, denoted as x, exhibits a collection of attributes that corresponds to the quantity of elements in the input layer, labelled as h0. The veiled layer is composed of M layers of Restricted Boltzmann Machines (RBMs) and N layers of Convolutional Restricted Boltzmann Machines (CRBMs). The number of instances in the label layer is equivalent to the number of classes represented in the label vector y. Currently, our methodology for determining the total quantity of hidden layers and the quantity of units inside each layer is based on empirical information and intuitive assessment. The primary goal of defining the parameter space W = w1, w2,..., wN for the deep architecture [53] may be seen as the task of determining the mapping function X!Y.

The Housing Development Board Nurses (HDBN) organises two separate training programmes. The construction of HDBN (Hierarchical Deep Belief Network) is carried out using a systematic and unsupervised approach, in which RBMs (Restricted Boltzmann Machines) and CRBMs (Convolutional Restricted Boltzmann Machines) are progressively stacked in a greedy fashion. The process of determining the parameter space W for N layers entails the use of both labelled data and all other accessible data. The HDBN employs an exponential loss function and uses gradient descent-based supervised learning for instruction. The use of labelled data (L) is employed to enhance the parameter space (W).

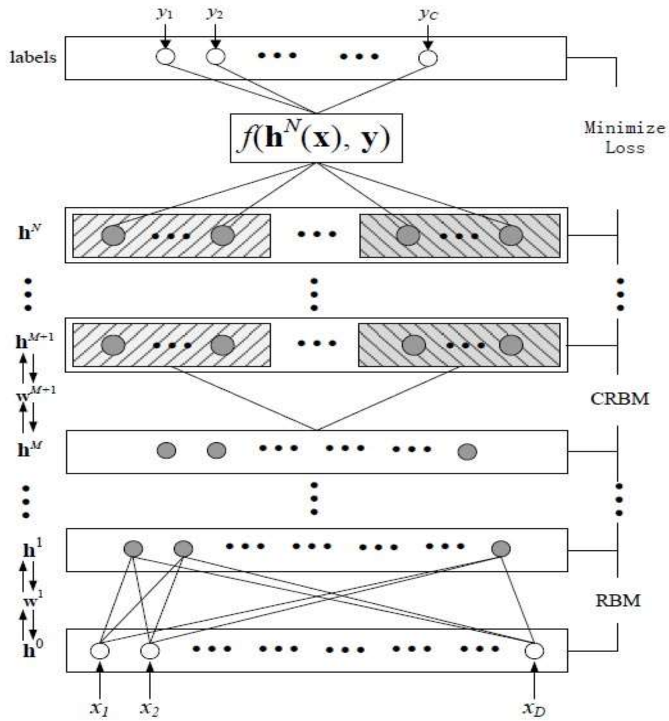

Figure 4: Architecture of HDBN.

5. Conclusion

The use of deep learning techniques in the analysis of user sentiment is a burgeoning field of study that is seeing substantial expansion. The data submitted by users is subjected to processing using a deep learning model in order to generate a potential user rating. This rating may then be used for the purpose of providing recommendations. The present study examines the efficacy of several deep learning architectures, including RNN, LSTM, DBN, and HDBN, within the domain of sentiment analysis. Numerous deep learning algorithms have shown superior performance in sentiment analysis in comparison to other methodologies. The continuous progress in deep learning research and its practical implementations is anticipated to provide further opportunities for the use of deep learning methods in the field of sentiment analysis.

References

[1]. P. Sasikala, L. M. I. Sheela, Sentiment analysis of online product reviews using DLMNN and future prediction of online product using IANFIS, J. Big Data, 7 (2020), 33–53.

[2]. P. A. Pavlou, A. Dimoka, The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation, Inf. Syst. Res., 17 (2006), 392–414.

[3]. A. Abbasi, H. Chen, A. Salem, Sentiment analysis in multiple languages: feature selection for opinion classification in web forums, ACM Trans. Inf. Syst., 26 (2008), 12–21.

[4]. Z. Zhang, Y. E. Qiang, Literature review on sentiment analysis of online product reviews, J. Manage. Sci. China, 13 (2010), 84–96.

[5]. C. Chang, C. J. Lin, LIBSVM: A library for support vector machines, ACM Trans. Intel. Syst. Technol., 2 (2011), 1–27.
[6]. F. Hu, L. Li, Z. L. Zhang, et al, Emphasizing essential words for sentiment classification based on recurrent neural networks, J. Comput. Sci. Technol., 32 (2017), 785–795.
[7]. Y. Mejova, P. Srinivasan, Exploring feature definition and selection for sentiment classifiers. In Proc. 5 th Int. Conf.
[8]. weblogs social media, Barcelona, Catalonia, Spain, (2011), 17–21.
[9]. W. Casey, G. Navendu, A. Shlomo, Using appraisal groups for sentiment analysis. In Proc. ACM SIGIR Conf. Inform. Knowl. Manag., (2005), 625–31.
[10]. L.-C. Yu, H.-L. Wu, P.-C. Chang, H.-S. Chu, Using a contextual entropy model to expand emotion words and their intensity for the sentiment classification of stock market news, Knowl. Based Syst., 41 (2013), 89–97.
[11]. I. Jolliffe, N. A. Jolliffe, Principal Component Analysis. Springer Series in Statistics, 2nd edition, Springer-Verlag, New York, 2002.
[12]. D. Adnan, F. Song, Feature selection for sentiment analysis based on content and syntax models, Decis. Support Syst., 53 (2012), 704–11.
[13]. L. G. Thomas, S. Mark, M. B. David, B. T. Joshua, Integrating topics and syntax, Adv. Neural Inf. Process. Syst., (2005), 537–544.
[14]. A. Yadav, D. K. Vishwakarma, Sentiment analysis using deep learning architectures: a review, Artif. Intell. Rev., 53 (2020), 4335–4385.
[15]. S. Kim, E. Hovy, Determining the sentiment of opinions. In Proc. Conf. Comput. Linguis., Geneva, Switzerland, (2004), 1367–1373.
[16]. P. D. Turney, M. L. Littman, Measuring praise and criticism: Inference of semantic orientation from association, ACM Trans. Inf. Syst., 21 (2003), 315–346.
[17]. Y. L. Zhu, J. Min, Y. Q. Zhou, Semantic orientation computing based on HowNet, J. Chin. Inf. Process., 20 (2006), 14–20.
[18]. G. Somprasertsri, P. Lalitrojwong, Mining feature-opinion in online customer reviews for opinion summarization, J. Univ. Comput. Sci., 16 (2010), 938–955.
[19]. B. Liu, Sentiment analysis and opinion mining, Synth. Lect. Hum. Lang. Technol., 5 (2012), 1–167.
[20]. B. Pang, L. Lee, S. Vaithyanathan, Thumbs up? sentiment classification using machine learning techniques. In Proc. Conf. Empir. Methods Nat. Lang. Process., Philadelphia, USA, (2002), 79–86.
[21]. A. Go, R. Bhayani, L. Huang, Twitter sentiment classification using distant supervision, CS224N Project Report, Stanford, 1 (2009), 1–12.
[22]. M. Guerini, L. Gatti, M. Turchi, Sentiment analysis: How to derive prior polarities from SentiWord Net, arXiv preprint arXiv: 1309.5843.
[23]. A. Tripathy, A. Agrawal, S. K. Rath, Classification of sentiment reviews using n-gram machine learning approach, Expert Syst. Appl., 57 (2016), 117–126.
[24]. Y. KIM, Convolutional neural networks for sentence classification, arXiv preprint arXiv: 1408.5882.
[25]. K. Cho, B. van Merrienboer, D. Bahdanau, On the properties of neural machine translation: encoder-decoder approaches. In Proce. Eighth Workshop Syntax, Semant. Struct. Stat. Trans., Doha, Qatar, (2014), 103–111.

[26]. Z. Qu, Y. Wang, X. Wang, A Hierarchical attention network sentiment classification algorithm based on transfer learning, J. Comput. Appl., 38 (2018), 3053–3056.

[27]. J. Pennington, R. Socher, C. D. Manning, GloVe: Global vectors for word representation, Proc. Int. Conf. Empir. Methods Nat. Lang. Process., (2014), 147–168.

[28]. F. Abid, M. Alam, M. Yasir, C. Li, Sentiment analysis through recurrent variants latterly on convolutional neural network of twitter, Future Gener. Comput. Syst., 95 (2019), 292–308.

[29]. J. Trofimovich, Comparison of neural network architectures for sentiment analysis of Russian tweets, In Proc. Int. Conf. Dialogue 2016, RGGU, (2016).

[30]. Q. Qian, M. Huang, J. Lei, X. Zhu, Linguistically regularized LSTMs for sentiment classification. In Proc. 55th Ann. Meet. Assoc. Comput. Ling., 1 (2016), 1679–1689.

[31]. L. Nio, K. Murakami, Japanese sentiment classification using bidirectional long short-term memory recurrent neural network. In Proc. 24th Ann. Meeti. Assoc. Nat. Lang. Process., Okayama, Japan, (2018), 1119–1122.

[32]. M.-L. Zhang, Z.-H. Zhou, A review on multi-label learning algorithms, IEEE Trans. Knowl. Data Eng., 26 (2014), 1819–1837.

[33]. J. Devlin, M. W. Chang, K. Lee, K. Toutanova, BERT: Pre-Training of deep bidirectional transformers for language understanding, In Proc. 2019 Conf. North Am. Chapter Assoc. Comput. Linguist. Human Lang. Tech., (2019), 4171–4186.

[34]. S. Seo, C. Kim, H. Kim, et al, Comparative study of deep learning based sentiment classification, IEEE Access, 8 (2020), 6861–6875.

[35]. B. Dzmitry, C. Kyunghyun, B. Yoshua, Neural machine translation by jointly learning to align and translate, In Proc. Int. Conf. Learn. Representations 2015, San Diego, CA, USA, (2015), 1–15.

[36]. D. Li, F. Wei, C. Tan, Adaptive recursive neural network for target-dependent twitter sentiment classification, Baltimore: Assoc. Comput. Ling.-ACL, (2014), 49–54.

[37]. S. M. Gr .er-Sinopoli, C. N. Thalemann, Bidirectional recurrent neural networks, IEEE Trans. Signal Process., 11 (1997), 2673–2681

[38]. S. Zhang, X. Xu, Y. Pang, J. Han, Multi-layer Attention Based CNN for Target-Dependent Sentiment Classification, Neural Process. Lett., 51 (2020), 2089–2103

[39]. K. Saranya, S. Jayanthy, Onto-based sentiment classification using machine learning techniques. In Proc. 2017 Int. Conf. Innovations Inf., Embed. Commun. Syst., (2017), 1–5. 39. S. Tan, J. Zhang, An empirical study of sentiment analysis for Chinese documents, Expert Syst. Appl., 34 (2008), 2622–2629.

[40]. W. Li, F. Qi, Sentiment analysis based on multi-channel bidirectional long short term memory network, J. Chin. Inf. Process., 33 (2019), 119–128. 41. Y. Yang, H. Yuan, Y. Wang, Sentiment analysis method for comment text, J. Nanjing Univ. Sci. Tech., 43 (2019), 280–285.