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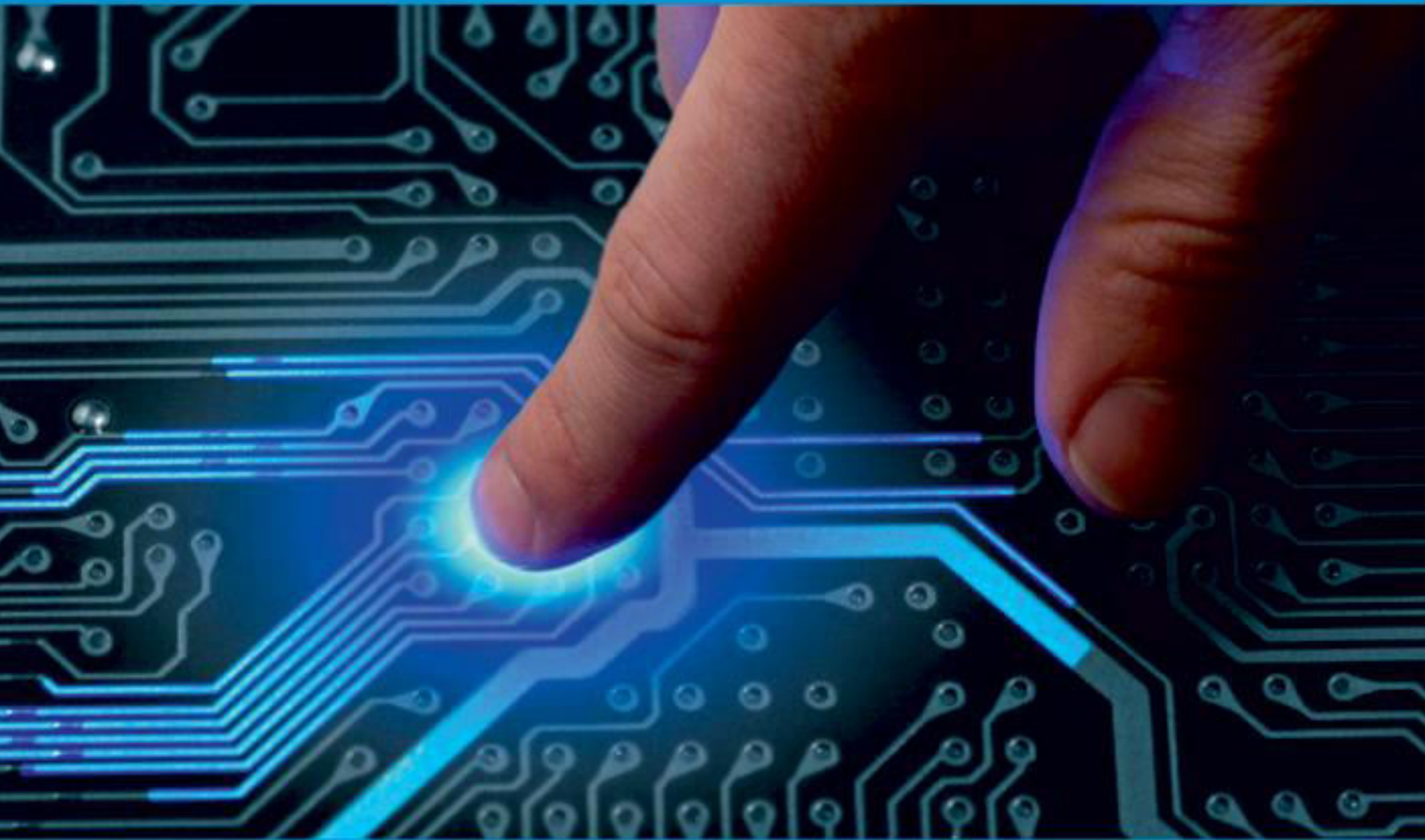

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User Rating Classification via Deep Belief Network Learning and Sentiment Analysis

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ABSTRACT: For natural language processing tasks like sentiment classification, deep learning models have been doing quite well recently. Recommender systems value user feedback because it contains a variety of emotional data that might influence the recommendation's accuracy or precision. For user suggestions, a deep learning model is utilised to evaluate user comments and provide an estimated user rating. Deep learning models are pre-trained in this work utilising the Hybrid DBN technique. Afterwards, we compare this to different deep learning algorithms.

KEYWORDS: Sentiment Analysis; Classification; Deep learning Algorithms; DBN;

I. INTRODUCTION

There is no fixed infrastructure in Mobile Ad Hoc Networks (MANETs), which is made up of mobile nodes that are independent of one another. Nodes in a MANET may communicate with one another and move around freely. In the event of an emergency, natural catastrophes, or military activities, MANETs are an excellent choice since they can be deployed quickly and are straightforward to set up.

Even if a user doesn't explicitly express their displeasure with a product or service, it might still be useful to know what they think. Other approaches, such as those based on the similarity of the outcomes, may be employed instead of machine learning [1]. Social media sites such as Twitter, Facebook, and Instagram are rich sources of data for sentiment analysis (SA). Since of this, while adopting the "big data" method, various sorts of data sources must be taken into consideration because there are more things to consider in order to store, retrieve and analyse the data rapidly and ensure that the findings are correct [2].

It is becoming more and more common for researchers to focus on automatic sentiment analysis (SA). No matter how popular or widely used SA is, there are still several issues with natural language processing that need to be addressed (NLP). It's still difficult to tell which side of an argument someone is on when using sentiment analysis, despite recent research [3,4] dealing with theoretical and technological issues. Hussein et al. [4] investigated the impact of these factors on sentiment structure and accuracy. This study demonstrates that current research on sentiment analysis place a high value on accuracy. A few issues, such as dealing with negation or domain dependency, are also highlighted.

As a result, social media is a valuable source of information for South Africa. Information is becoming more complex and interconnected as social networks continue to expand.

Ideas for sentiment analysis using deep-learning methods have emerged in recent years. The characteristics and degrees of performance of these analyses vary. Recent experiments using deep learning models including deep neural networks (DNN), recurrent neural networks (RNN), and convolutional neural networks (CNN) to handle various sentiment analysis challenges are examined in this paper (e.g., sentiment polarity and aspect-based sentiment). On Twitter datasets, the finest deep learning-based algorithms to sentiment analysis were implemented, including TF-IDF and word embedding.

A. Incorporating a word

Many deep learning models in NLP use word embedding findings as features [5]. It is possible to learn about language aspects by embedding words in a model of the language. It transforms the words in a lexicon into vectors of real values that may be interpolated. "Hat" is an example of this (..., 0.15,..., 0.23,..., 0.41,...) Methods for embedding from high-dimensional sparse vector spaces (such as one-hot encoders) to lower-dimensional denser vector spaces are often used. Using the embedding vector, it is possible to reveal a word's hidden properties. The patterns and regularities of language may be stored in the vectors.

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Learning how words are constructed may be accomplished via the use of neural networks [6, 9] or matrix factorization [10]. Word2Veci is a popular word embedding method. Computers may use it to anticipate word embeddings from texts using a neural network model. CBOW and SG models are both available. Based on the context, the CBOW model predicts the target word, such "wearing," based on the surrounding terms, such as "the boy is wearing a hat." According to the SG model, the words around the target word are predicted using just the target word. The CBOW model smooths over a lot of information about how items are distributed by treating the whole context as one observation. Because of this, it is well-suited for use with much smaller datasets. Each pair of context and target is treated as a new observation in the SG model, which is better suited to huge datasets. Another approach often used is Global Vectorii (GloVe) [11]. A global word-word co-occurrence matrix is used to train it.

FFT is employed to minimise truncation artefacts and aliasing artefacts in the proposed study [7] [8] [9]. Finally, the cerebellum is scanned using Fuzzy C means and Level set techniques of segmentation [12] [13] [14].

II. RELATED WORK

As a starting point for future empirical research, this study aims to examine several methodologies and methods for sentiment analysis. Each study's methodologies and applications have been narrowed down to only a few key components that we feel are essential to the research process.

Sentiment analysis tasks have become more efficient because to the usage of deep learning models like DNN, CNN, and RNN. Sentiment analysis methods based on deep learning are discussed in this section.

Several academics have studied this tendency since 2015. Deep learning algorithms for sentiment analysis were developed by Tang et al. [12]. Learning word embedding, identifying sentiment, and extracting opinions are just some of the strategies that may be used. To understand how individuals feel, Zhang and Zheng [13] discussed employing machine learning. TF-IDF was employed to calculate the weight of words in the study, while POS was utilised as a text feature by both research groups. To better understand human emotions, Sharef et al. [14] examined the potential of big data in this area. Sentiment analysis difficulties were examined and contrasted in publications [15–17] using the most recent deep-learning-based algorithms (CNN, RNN, and LSTM).

Deep learning-based sentiment analysis has been utilised in numerous sectors, such as finance [18, 19], weather tweets [20], travel advisers [21], cloud service recommender systems [22], and movie reviews [23]. The Word2vec programme was used in [20] to embed user input and weather information into words, which was collected from several data sources. The same techniques have been employed in a number other works [24]. By combining the findings of a consumer sentiment analysis with topic modelling, Jeong et al. [25] discovered strategies to enhance goods. A real-time monitoring tool has been utilised in contexts where goods change fast to see how consumer requirements change. Researcher Pham and his colleagues studied travel evaluations to find out what customers thought about the value, location, cleanliness and service of a hotel.

Emotion detection is employed in another approach [26] which incorporates sentiment and semantic information into the algorithm. Preethi et al. [22] employed deep learning to do sentiment analysis for a cloud-based recommender system based on Amazon's food dataset. Ontology-based aspect-level sentiment analysis was utilised by Salas-Zárate et al. [27] to analyse tweets concerning diabetes in the health domain. There was a study that employed deep learning to analyse tweets based on their polarity [28].

Using deep learning models, the authors were able to improve their own sentiment analyses. In addition to English-language tweets, certain models can also handle tweets in other languages, such as Spanish (29), Thai (30), and Persian (31), among others.

When studying tweets, researchers have utilised a variety of polarity-based sentiment deep learning models in the past. These models include DNN, CNN, and hybrids.

Neural network models are also used in other studies that look at the text's sentiment in terms of polarity as well as the text's other features.

It was found that Salas-Zárate et al. [27] employed semantic annotation (the diabetes ontology) to identify attributes. SentiWordNet was utilised to do sentiment analysis based on the aspect data. Pham et al. [21] investigated the importance of product attributes by asking participants how they felt about them. It was suggested to use a multilayer architecture to get stronger sentiment characteristics in order to portray customer evaluations in a new manner.

Using data from 32 research, we discovered that deep learning may be used to determine the polarity of sentiment using three methods: DNN, CNN, and hybrid. CNN, RNN, and LSTM were evaluated on their own datasets using three different deep learning algorithms. However, there was no way to compare and contrast the three approaches.

Many research use the same approach to determining how individuals feel. The first step is to extract text characteristics from a variety of data sources. The text characteristics are then embedded into the words using the Word2vec tool.

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Sentiment analysis has been extensively studied in the context of recommender systems. Content-based (CB), collaborative filtering (CF), demographic-based (DB), and hybrid approaches are the most common in this field. You may utilise social media data in a variety of ways by using these techniques. CF approaches employ implicit or explicit user preferences, demographic methods use user demographic information (age, gender, country, etc.), and hybrid methods use any sort of item and user information that may be retrieved or inferred from social media (actions, preferences, behavior, etc.).

Recommendation systems may also utilise hybrid approaches and lifetime learning algorithms to cope with both explicit data (input that users provide themselves) and implicit data (data that can be inferred from how users act and behave).

Using both content filtering and collaborative filtering, Shoham [32] developed one of the earliest hybrid recommendation systems. Identifying users based on their interests in web sites is the focus of the proposal's content-based component. Based on what other users have to say about a website is used for collaborative filtering in the system.

III. PROPOSED ALGORITHM

A. *Sentimental Analysis:*

As a branch of NLP, sentiment analysis aims to identify and categorise the various elements of a word using a model-based approach. Structured data may be derived from unstructured data on people's feelings about a wide range of topics, including goods, services, brands, politics, and a host of other topics. Using this data for marketing research, public relations, product evaluations and net promoter rating may be very beneficial to businesses.

In order to determine how satisfied or dissatisfied customers are with a product or service, sentiment analysis employs user comments. Sentiment analysis is built on top of opinion lexicons. An opinion lexicon is a vocabulary that includes terms like "happy," "good," "poor," or "disgusting" to indicate how positive or negative a term is. Sentiment analysis relies heavily on these opinion words to get a sense of what the user is thinking. Just a handful of the public dictionaries that have emerged in recent years are SentiWordNet [34], General Inquirer [35] and SenticNet [36]. Identifying the opinion targets (aspects, entities, and themes) is a critical initial step in sentiment analysis[37]. Building an opinion vocabulary is the next stage. For example, the service at this restaurant has been appalling. Despite the fact that the goal term is "disappointed," and the opinion word "disappointing" is also in the mix.

B. *Application of Sentimental Analysis:*

Sentiment analysis may be used to a wide range of industries, including business and government, as well as biomedicine.

As a result of consumer feedback, businesses may improve their customer service, develop better goods, or alter marketing techniques to attract more customers. Analysis of how people feel about events or items may be accomplished via the use of sentiment analysis. Using the findings of SA, we may learn more about what our clients are interested in or what they believe about industry developments." An SA framework for analysing the sentiment of Twitter data was devised by Jain and Dandannavar [38] utilising certain machine learning algorithms and Apache spark.

As said at the outset, recommender systems have benefited from sentiment analysis as well. Recursive neural networks were utilised in the work of Preethi et al. [40] to determine how individuals felt about reviews. To enhance and evaluate a cloud-based recommender system for restaurants and movies, the findings were included into the system. Commodity markets may benefit from sentiment research, which examines how individuals behave [41].

It's also feasible to pursue a career in the medical industry. Opinion mining in health-related social media and blogs was examined in [42]. Experts and patients alike may benefit from a medical vocabulary and innovative approaches to machine learning and text processing, which the author introduces alongside tried-and-true methodologies. As an alternative or addition to the standard questionnaires that patients fill out, sentiment analysis is used in the mental health area. For this, social media posts by patients are examined.

The Methods of Feature Extraction

It is common practise for Deep Learning algorithms to learn from characteristics that have previously been selected for use in training. They then make predictions based on the results of the tests. Nevertheless, the primary issue with

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processing language is the inability of Deep Learning algorithms to operate directly on raw text. As a result, we'll need some methods for extracting features from text in order to create a matrix or vector of features.
Some of the most common ways to pull out features are:
1. Bag-of-Words
2. TF-IDF

Bag of Words:
In order to transform a collection of tokens into features, Bag-of-Words is one of the most straightforward methods. The BoW model is used to categorise texts, and each word is utilised as a feature to train the classification system. Words like "fantastic," "great," and "excellent" may suggest a favourable review, whereas "annoying," "terrible," and other negative terms can indicate a bad review.

TF-IDF Vectorizer:
There's an acronym for this: TF-IDF, which stands for It raises a distinct concern that, although not often raised in our corpus, is still important. Each time a word occurs in a document, its TF–IFD value increases, and each time that word appears in a corpus, its TF–IFD value decreases. the two pieces that make it up are:
1. Term Frequency (TF)
2. Inverse Document Frequency (IDF)

C. *SentiWordNet Algorithm*

SentiWordNet: a sentiment lexicon for broad use Founded in 2006, SentiWordNet (SWN) is a global lexical resource. For each WordNet synset (sn), there are three number scores: Obj, Sub, and Negative (sn). "objective," "subjective," and "negative" are all used to describe these sets of words. 0 to 1 is the range of these scores, and the total of all of them is 1. If a synset is not zero in any of the three categories, it should be noted. In other words, only some of the concepts in the synset have the three opinion-related traits that are listed. The scores are based on WordNet synsets. This is accomplished via the employment of eight ternary classifiers. All of these classifiers are quite accurate in their classifications. In place of the Subjectivity-Objectivity labelling, this technique helps determine the semantic direction and the semantic strength of synsets. After analysing at how each synset's glosses are utilised, scores are determined. All of the synonyms on SentiWordNet have the labels Objective, Positive, and Negative because of SentiWordNet's broad reach.

IV. DEEP LEARNING MODELS FOR SENTIMENT ANALYSIS

Learning tasks may benefit from the usage of numerous layers of artificial neural networks (ANNs). A strong machine learning technique known as deep learning is applied in the research sector. It is capable of solving supervised and unsupervised learning problems by learning several layers of representations and abstractions from data [45, 46]. In order to locate and categorise features, deep learning requires multiple layers of processing units that do not function in a straight line. Sentiment analysis is a hot topic in the field of Natural Language Processing.

When it comes to sentiment analysis, there are both supervised and unstructured techniques available to use. Examples of supervised machine learning algorithms include support vector machines (SVM), maximum entropy, naive bayes, and others. Unsupervised machine learning approaches include sentiment lexicons, grammatical analysis, and syntactic patterns. There has been a recent uptick in the application of deep learning in sentiment analysis. Deep learning models are preferred because they provide more accurate and faster outcomes when used for learning tasks. In the future, deep neural network algorithms will be able to both extract features and organise documents and short words.

A. *Recurrent Neural Networks*

It is possible to employ recurrent neural network models to analyse natural language without depending on a window's dimensions. Different sentence lengths can be handled by most recurrent networks.

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Recurrent networks have a distinct technique of sharing parameters. The final output determines the output of the preceding output. Using the same update rule as before, each portion of the output is created. A tremendously complex computational graph [47] emerges from the repeated application of this formula. Fig. 1 depicts the three-step paradigm of a recurrent neural network.

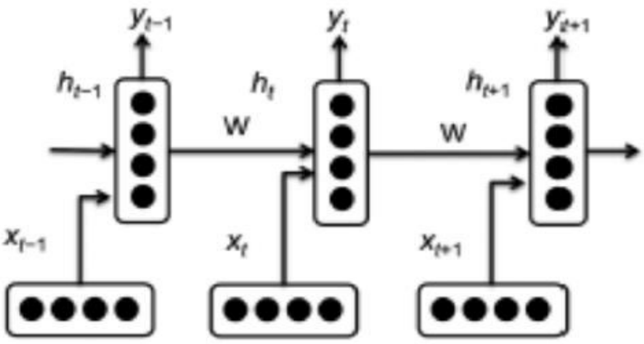

Fig 1: Recurrent Neural Network

B. *LSTMs*

RNNs known as "LSTMs," or long-term memory networks, are capable of learning long-term dependencies. While LSTMs are constructed similarly to RNNs, they contain more pieces than RNNs.

The horizontal line at the top of the figure, which represents cell state C(t), is the most important part of LSTMs. Besides h, a cell state is another method of storing information. " (t). C(t) indicates that unlike RNNs, LSTMs can handle significantly longer sequences.

LSTMs are also capable of altering the state of a cell by deleting or adding information. Gates are used to keep an eye on this activity. However, you can only open a gate if you're willing to do so. The state of a cell in an LSTM is protected and controlled by three of these gates.

Using the Forget gate, we can determine what has to be removed from the h(t-1) state so that we only maintain the most relevant information....

x(t) represents the current input to our cell, and at the input gate, we select whether to add fresh information to our cell, which is currently C. (t).

To put it another way, this gate determines what will be sent out of the cell, C(t), to C(t+1). 'Output Gate' A verb could be sent out in the language model example since it just observed a subject, and just in case that's what follows next. To give you an example, it may inform us whether the subject is single or plural so that we know how to conjugate the verb.

Nerve cells in a distinct network produce each of these conditions. Because of this, LSTMs are quite complicated. At this point, I won't go into any more detail on LSTMs.

To generate the document model, Tang [47] employs numerous layers of LSTMs. The document level LSTM receives the sentence vectors from the first LSTM layer and uses them to model sentences. Classification difficulties were easily solved with the help of the model. Neural machine translation (NMT), often known as LSTM, is another well-known use of LSTM Researchers often employ the sequence to sequence model. An encoder and a decoder, both LSTM chains, make up the model. The encoder encodes the input phrase, while the decoder guesses the next word based on the preceding ones. "" He employs this technique in Zaremba [48]'s work. No matter how you look at it, the same principle may be used to locate phrases that are related or similar, as shown by Sutskever [49].

An RNN known as long short-term memory (LSTM) may employ long memory as an input to activation functions in its hidden layer, making it a unique sort of RNN. They came up with this concept together (1997). The LSTM architecture is seen in Fig. 2. An embedding matrix is created by first altering the data in the input (the process is similar to the one described for the CNN). Another layer of LSTM has been added. In all, there are 200 individual cells. In the final layer, there are 128 cells that are utilised to categorise text. The last layer employs the sigmoid activation function to reduce the 128-dimensional vector to a one-dimensional output vector, due to the presence of two classes to be predicted (positive, negative).

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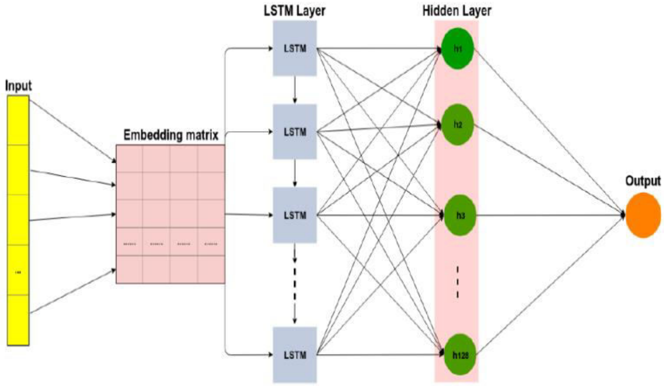

Fig 2: A long short-term memory network

C. Deep Belief Networks (DBN)

Layers of hidden units are linked together via linkages inside the layers to form a deep belief network (DBN). There are no connections between units in the same tier. The original input node may be used to choose the most essential attributes that will be utilised in the training phase as the input layer for DBN. Since the layers operate as feature detectors, their abilities are dependent on a probabilistic reconstruction of their input. DBN may also be utilised to solve classification issues based on its training model [51].

Values might be stored in leaf nodes without bias thanks to the use of Deep Belief Networks [52]. Training a layer of characteristics that can receive signals directly from the pixels is an important initial step. In the following phase, the values of this layer are treated like pixels, and the features of the previously learned features are learnt in a second hidden layer. Adding characteristics or features to a belief network improves the lower limit on the log probability for the training data set.

Only once a model has been trained entirely is the Test Dataset utilised (using the train and validation sets). The test set is most often used to compare various models. However, it does not display the anticipated result. It is possible to estimate the model's attributes by analysing the testing data. Using a fair amount of data, a final model's fit to the training dataset may be evaluated using a test dataset. The last stage is to make a prediction, and the text file submitted by the user serves as input. Before the input text file can be analysed for intent or domain, it is preprocessed, trained, and classified. Data from a training dataset is used to generate the sentences. The accuracy of a test is measured by the proportion of accurate predictions made based on the test results. Simple to deduce: just compute the ratio of correct answers to all possible guesses.

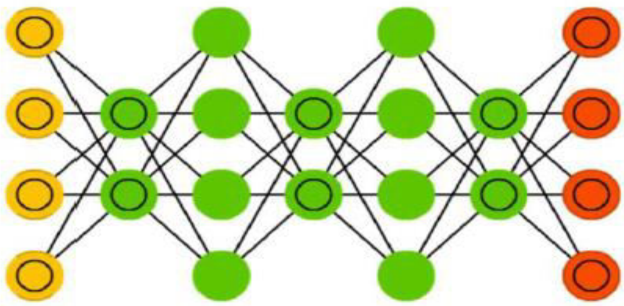

Fig 3: Deep Belief Networks.

D. Hybrid Deep Belief Networks (HDBN)

You may now learn without being constantly monitored by HDBN. Convolutional calculations are computationally intensive, hence RBM is used to minimise the dimension of the review using standard calculation before convolutional calculations. A fully connected directed belief net (HDBN) with one input (h0), N hidden layers (h1, h2,..., hN), and one label layer at the top is shown in Figure 4. Units in input layer H0 are equal to the number of features in review x.

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The concealed layer is composed of N M RBM layers and M M CRBM layers. The label layer's number of units is the same as the label vector y's number of classes. There are now a limited amount of hidden layers and a limited number of units per hidden layer. Finding the mapping function X!Y becomes a matter of locating the deep architecture's parameter space W = w1, w2,...,wN [53].

The HDBN's training is divided into two stages:

Unsupervised, greedy layering of RBMs and CRBMs is used to construct HDBN. L labelled data and all other data are utilised to discover the parameter space W with N layers.

Based on the exponential loss function, Gradient Descent-based supervised learning is utilised to train HDBN. W parameter space may be improved by using L labelled data.

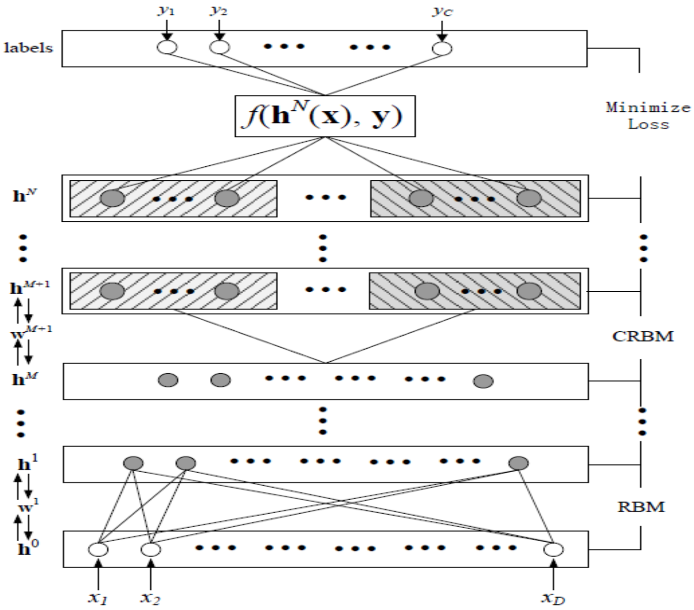

Fig 4: Architecture of HDBN

V. RESULTS

The results of the test are shown below:

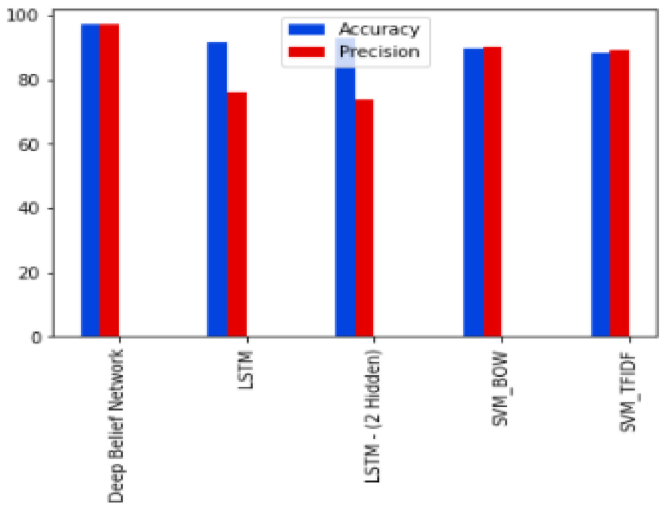

Fig 5: Accuracy Graph

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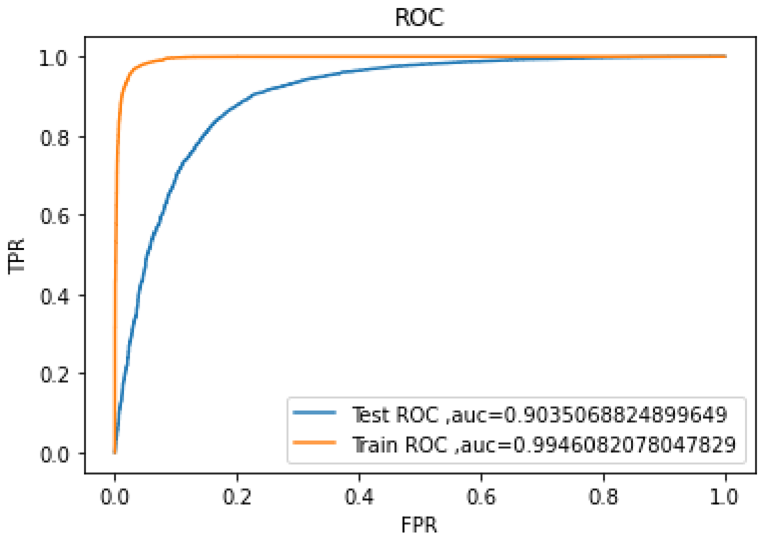

Fig 6: ROC graph

VI. CONCLUSION AND FUTURE WORK

The hybrid DBN method was compared to all other deep learning algorithms in the suggested study. The hybrid DBN algorithm performed better than any of the other methods. In this paper, we propose a novel method for predicting how users would score something based on the way they speak about it. To create the feature vector, the sentiment analysis takes into account user sentiment and what they say about a product or service in their remarks. There are also mechanisms in place to remove brief comments, those that don't add anything to the discussion, and those that incorrectly rate a product. Experimentally, the DBNSA model outperforms alternative baseline models. Training loss value, preciseness and recall are also better than baseline models on the Yelp and Amazon datasets. MLP has the greatest precision, libSVM the best accuracy, MAE, and F-score, and DBNSA the best MSE training loss value and recall in the TripAdvisor data set. Faster than the other baseline approaches, and saves more time, DBNSA is better. In the future, we want to investigate how social interactions effect comments on a user's timeline, since comments are influenced by how well individuals know each other.. If you've used comparable items or services before, you may be affected by what you've done in the past. Time is another factor to consider while dealing with the issue of cold start. Cold-start may be an issue that may be solved by knowledge from a different timeframe. It's also important to consider the phenomenon known as sarcasm, which occurs when individuals offer evaluations based on the opposite of what they really mean. Most methods for finding sarcastic remarks are difficult to utilise. Because the suggested approach is currently too slow to test in real time, we are working to speed up the calculations. A rapid deep learning system will be used for real-time testing.

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