# A Study of Sentiment Analysis for Movies Reviews Using Deep Neural Network.


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**bstract- Sentiment analysis is a popular and growing topic of research in natural language processing (NLP) and text mining.It is quickly becoming one of the most important and exciting fields of research because the success of a product is largely determined by how well it is rated online. Sentiment analysis helps us to determine how natural text connects to how people feel or think. It allows us to observe how a person thinks about something very important to the person who created it. Nobodygoes to the movies anymore unless they've heard positive things about it on social media or from film critics. The same is true when purchasing something. As a result, reviews are becoming an important aspect of marketing. it is important to make it easier and less error-prone to infer the sentiment of a review.**



**Keywords- natural language processing, film critics, quickly etc**


## I. INTRODUCTION

NLP is a computer program's capacity to understand spoken and written human language, often known as natural language. It's a part of AI (artificial intelligence). The rapid increase of user-created data on the internet necessitates the development of an effective approach for extracting relevant data. This condition emphasizes the relevance of text classification, which is the process of classifying texts into appropriate groups based on their content.

In recent years, sentiment analysis (SA) has gotten a lot of interest from scholars as a hot topic in NLP research. The method of discovering the emotional tones behind a string of words is known as sentiment mining or analysis. Sentiments are based on a set of values for features such asbi-grams and tri-grams, as well as their polarities and combinations. Their influences are gradual and repetitive. So, to continue working on the neural network's hidden layer, a kernel function that assesses the existence of class labels is used [2]. SA is a method for defining whether datais good, negative, or neutral using NLP. SA models consider not just polarity, but also sentiments and emotions, urgency, and even intents [3]. Figure 1 shows thefeatures of sentiment analysis.


Figure 1 Sentiment Analysis Features [4]

SA is often carried out on three phases: phrase level, document level, and aspect level. The goal of document-level sentiment categorization is to assign a favorable or negative rating to the entire document or topic. Sentence level sentiment classification reflects the polarity of individual sentences in a document, whereas aspect level sentiment classification first finds the various characteristics of a corpus and then calculates the polarity of each text about the collected aspects [5].

## II. TYPES OF SA

Different methods of SA are utilized in the market to understand people's feelings. Other sorts of SA, in addition to regular opinions - positive, negative, or neutral – aid in comprehending people's underlying feelings, genuine intentions, and emotions.

**1. Fine-grained sentiment**

This is among the most basic and often used methods of determining client sentiment. This analysis gives us a better grasp of the client comments we've received. The sentiments are categorized using publicly available categories such as good, neutral, and negative. Another way to scale consumer input is to provide a rating choice ranging from 1 to 5. This method is used by the majority of e-commerce sites to determine their clients' feelings.

**2. Emotion detection SA**

This is a more sophisticated approach to identifying emotion in a text. This type of analysis aids in detecting and comprehending people's emotions. Anger, sadness, happiness, frustration, fear, panic, and concern are all possible emotions to include. The benefit of employing this is that an organization can better understand why a consumer feels a certain way. However, analyzing people's sentiments via emotion detection is challenging since individuals use a variety of phrases with varied meanings, such as sarcasm.

**3. Aspect-based analysis**

This sort of SA is primarily focused on the features of a certain product or service. Aspect-based SA is critical because it can assist enterprises in automatically sorting and evaluating client data, as well as automating procedures such as customer support chores, allowing us to acquire valuable insights on the go. Aspect-based SA enables businesses to pinpoint the aspects of their productsor services that their customers are dissatisfied with and aids them in gradually resolving those concerns. Problems with new software programs, such as malfunctions or serious problems, can also be handled. Intent-based SA The automatic classification of textual material based on the customer's intent is known as intent classification. An intent classifier can naturally deconstruct documents and reports and classify them into intentions such as purchase, downgrade, and unsubscribe, among others. This is useful for deciphering the intents behind a huge number of client questions, automating measures, and gaining valuable experience. When it comes to areas like customer assistance and sales, intent classification allows firms to bemore customer-friendly. It enables them to respond to leads more quickly and handle big numbers of queries.

## III. RELATED REVIEW

**NhanCach Dang et al. -** looked at the effects of various datasets, feature extraction approaches, and DL models, with a particular focus on sentiment polarity analysis. When implementing a SA, the results demonstrate that combining DL approaches with word embedding is preferable to using TF-IDF. In addition, the trials demonstrated that CNN outperformed other models, offering a solid mix of accuracy and CPU runtime. With most datasets, RNN reliability is slightly higher than CNN reliability, but its computing time is substantially longer. The conclusion reached was that the efficiency of the algorithms is mostly determined by the Combination of 29 dataset attributes, implying the utility of testing DL approaches with more datasets to cover a wider range of characteristics [1].

**Alhassan Mabrouk -** The Sentiment Classification (SC) problem, which is core work in reviews mining or SA, has been solved using recent DL techniques. Different factors have an impact on the performance of various approaches. These characteristics are classified into three groups in this paper: data preparation-based factors, feature representation-based factors, and classification techniques-based factors. The study is a comprehensive literature- based survey that analyses the performance of over 100 DL-based SC techniques using 21 publicly available datasets of customer reviews from three different application domains (products, movies, and restaurants). These 21 datasets have a variety of qualities that help us see the big picture of our research. The comparison demonstrates how the recommended criteria have a quantitative impact on the performance of the DL-based SC techniques under consideration [2]

**Kalaivani A and Thenmozhi -** A fundamental objective in SA is to determine if the expressed ideas in a sentence, a document, or another entity aspect/feature are negative, neutral, or positive by categorizing the polarity of the presented text at the sentence, document, or aspect/feature level. This report also includes a literature review of the various DL approaches used in SA. The significance of SA is also defined. In addition, the many types of classification processes are briefly mentioned, as well as their limits. This literature review illuminates the many existing SA methods suggested by various scholars, whichwill aid future researchers in this field [3].

**Rakhee Sharma et al. -** investigated the use of several modalities for categorizing the polarity of opinions in internet videos, as part of a multimodal SA task. Experiments were carried out using a freshly introduced dataset. Analysis s using simple text reveal that the CNN model outperforms the RNN model and that utilizing pre- trained word embedding is advantageous. They also examined the text method's portability, demonstrating that substantial progress can be obtained using a second CNN model. While further research is needed to look at datasets from different areas and languages, they feel their preliminary findings demonstrate that this research direction has promise. [4]

**Alexander Ligthart et al. -** This paper presents the findings of a tertiary study on SA methodologies, with the goal of highlighting the adopted features (input/output), methodology, data sets, and obstacles in SA. The responses to the research questions were collected from extensive secondary research. The most significant obstacles in SA, according to this study, are domain and language reliance. Different languages and fields of interest require different text corpora. There have been attempts to create cross-domain and multi-lingual SA models, but this difficult work needs be pursued further [5].

**Abhinandan P Shirahatti and Krupa -** present a full examination of DL (DL) and its applications, such as emotional analysis and NLP. For SA, DL has an advantage over traditional ML algorithms like support vector machine (SVM) and Nave Bayes because of its ability to overcome the challenges of SA and handle the uniqueness involved without the costly requirement for manual feature engineering. DL models promise one thing: given enough data and enough training time, they will be able to do sentiment classification on any text class with minimal limits and no task- or data-specific manual feature engineering. They believe that this survey will be a useful resource for new DL practitioners as well as those looking to innovate in their use of the technology [6].

**IndhraomPrabha M and Umarani -** At both the phrase and aspect levels, they offered a detailed overview of various DL architectures utilized in SA. The benefits and cons of several state-of-the-art techniques are also examined. They realized that the approaches' success varies depending on the application. Because there is a lack of consistency in terms of evaluation methodology, it is impossible to determine which technique produces the best results for each domain based on existing state-of-the-art methodologies [7].

**Qi Wang et al. -** They gained an understanding of the fundamentals of generally used neural network models andhow to implement them in NLP as a result of this experiment. This paper exclusively uses the movie review dataset for SA. Various fields have different terminology and description methods in other text datasets, so the difference in sentiment orientation in different types of text data is clear. Different applications can create their corpus in various sectors, allowing for a more accurate SA of the text. The accuracy can be enhanced more through model merging and parameter tuning in DL neural networks [8]

**Arnab Roy &Ojha -** For Twitter SA, they applied three well-known DL models and preprocessed data to reduce noise from the data and improve the accuracy of the model. They also analyzed these models and examined their performance on test data, discovering that the BERT model outperformed the others. BERT's greater performance can be attributed mostly to a pretrained Wikipedia language model and a book corpus that provides a clearer comprehension of the English language and hence outperforms the other two classifiers [9].

**Siddhartha Mukherjee -** demonstrated that on Hind-English, late-fusion of learned character and word with suggested DLACMT outperforms baseline character-only classification task, demonstrating its resilience with various loss functions and optimizers. The study also discusses the issue of word embedding for code-mixed corpora. The method for preparing a corpus for word code-mixed text training. This method involves resource languages, with a focus on Indic code, and it has been observed that it improves corpus accuracy. The suggested method applies to opinion mining and other text mining tasks on a variety of social media platforms for sociological and business goals [10].

**Enas A. H. Khalil-** Using NLP, computational linguistics, and text analysis, SA or opinion mining gathers and analyses subjective information from numerous sourcessuch as the web, social media, and other sources to determine people's opinions. This examined data reveals the public's feelings or attitudes toward specific products, people, or ideas, as well as the contextual polarity of the data. This comprehensive overview gives a detailed overview of recent SA research. It also describes the various methodologies used and the numerous applicationsof SA systems. With a total of 156 papers analyzed and graded in this systematic review, 99 publications meet their research requirements in Science Direct, while 57 papers meet the same conditions in Springer. The domain, methodologies, performances, and language have all been examined [11]

**VishuTyagi et al. -** provide an elevated summary of the Sentiment140 Twitter datasets. They suggested a unique method for analyzing tweets from a tagged twitter dataset as a Negative or Positive class using DL neural networks and CNN-LSTM approaches. They employed an effective DL architecture with optimized hyper parameters on CNN layers and Bidirectional LSTM neural networks with long-range dependencies in this model. On our benchmark dataset, the model outperformed all baseline techniques. The proposed model has an accuracy of 81.20 percent [12]

**Shilpa P C et al. -** Modelled a method for analyzing the sentiment of tweets. The tweets they are looking at in this research are a combination of words and emotions. They created a model of the classifier. RNN and LSTM are two DL approaches. They used different feature selection approaches, such as TF-IDF and Doc2Vect, to improve accuracy. The feature extraction produces a vector, which is fed into the classification model as an input. When it came to classifying Twitter emotional tweets, the model performed better [13]

## I. PROPOSED METHODOLOGY

### 1. Deep Neural Network

Representation learning, a method of deep learning that builds on previous theories, aims to learn acceptable features or representations automatically. When it comes to solving machine learning problems, deep learning has a number of advantages over approaches that rely heavily onhuman-engineered features. Because of latent patterns that even subject matter experts cannot detect, human- engineered features are frequently exceedingly specific and often incomplete. It takes a long time just to design and validate a feature. Unlearned representations and features are less adaptable and require more time to learn. In terms of generalization, the deep learning framework is adaptable and can be used to learn information that is based on real-world, time-dependent, visual, and linguisticinputs. As depicted in Figure 1, an n-layer deep learning network. The layers consist of an input layer, m-hidden layers, and an output layer.

### 2 1D Convolution

An algorithm known as 1D CONV can be applied to a wide range of tasks, including time series analysis. Activation functions can be found in an input layer, an output layer, and a random number of hidden layers. The input layer is responsible for receiving and transmitting three-dimensional input to the hidden layer. Hidden beneath the model's surface is the model's computer. The Conv1D layer, the max-pooling layer, and the dropout layer can all be used in combination, depending on the situation. The Conv1D layer is CNN's most fundamental building block. The height of the filter is determined by the features that are removed from the input signals. Data is extracted from a sequence by training the model on the specified dimensions. In equation (1), the formula for determining output dimensions.

$n_{out} = [\underline{n_{in} + 2p-k}] + 1$ ……..(1)

Where, $n_{in}$ = input size, $n_{out}$ = output size, k= kernel size, p= padding size, s= stride size

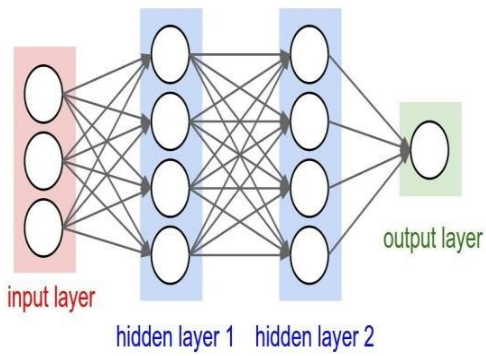
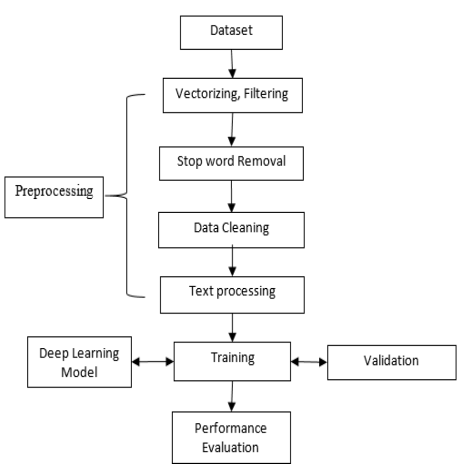



Figure 2 Generic Deep Neural Network

## IV. PROPOSED FLOWCHART




## V. CONCLUSION

Deep learning is a subset of machine learning that use neural networks in a novel way. A normal neural network, in other words, is a single network with hidden layers in between the input and output layers where calculations are performed. Deep Neural Networks are made up of many neural networks, with the output of one network becoming the input to the next, and so on. This concept solved the problem of Neural Networks working too many hidden layers and made it easier to work with large amounts of data. Deep learning networks, which have evolved as a robust machine learning technique that learnsseveral layers of data features and predicts the features on their own, are known to learn the features on their own. Deep learning has recently been used in a range of signal and information processing applications as big data has grown. Deep learning networks have also been used for sentiment analysis and opinion mining.

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