Utilization of deep learning and semantic analysis for opinion mining in information extraction: a review

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ABSTRACT

In concern of the increasing availability and popularity of the opinion information sources at a different platform like individual blogs, online feedback, and social network are proliferating and gaining new opportunities and challenges that can be actively exploited using information technology to seek and comprehend people's opinions. In today's field people or entrepreneurs before taking any decision they must be considering the opinion of peoples or information networks. Most of them express the view or opinion through social media platform like Tweeter, Facebook, or blogs on the internet. Therefore, it is essential to analyze to automatically analyze the immense amount of social data available on the internet. Deep learning (DL) has appeared as an influential machine learning (ML) method that studies the properties of different layers or data and provides more advanced predictive results. The study of DL, along with success in many other practical fields, has been widely used in opinion and emotion analysis in recent years. This review explores new challenges in brainstorming and facilitates DL study and the use of semantic analysis. The analysis focuses mainly on methods that try to solve new challenges identified by empathy programs, compared to those already in place. It also conducts extensive research on its current uses in emotion analysis.

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1. INTRODUCTION

The rapid emergence of work in the field of opinion, emotion, and the subjective computer-aided approach to opinion and emotion analysis in the text arose as a direct reaction to the growing concern in at least current systems that deal directly with opinions as a prime object. Companies and organizations constantly want to locate the customer or communal opinions regarding their products and packages. So, it is essential to design a system which can automatically process and classify the vast amount social and online data to support in different domain like e-commerce, movie review, and tourism. The analysis of opinion or emotions, the processing of natural languages (NLP) [1]-[3] through the automatic extraction of views, opinions, and feelings from the text, speech, and database. This research paper reviews the supervised methods that divide opinions into positive (POS) or negative (NEG) groups.

Semantic analysis (SA) and opinion mining is a field that analyses people’s thoughts, feelings, assessments, attitudes, and feelings in writing. This is one of the most active fields of research in NLP, as well as extensive research in data mining, web development, and text mining. This research has extended because of its importance for business and society as a whole to the computer science management sciences and the social sciences [4]-[6]. The emerging significance of opinion analysis (OA) coincides in line with social development platforms like Twitter, Blogs, and Instagram. It is an upbringing practice that a large community of people sharing their views in writing and express their opinion which can be utilized for various analysis. These systems are used in nearly every activity and social organization. This is because opinions are essential to nearly every individual activity and have a huge impact on our behaviour [7], [8]. It is common beliefs and attitudes of peoples that they mostly depend on how others see and value the objects and opt for their choice accordingly. That's why it often seeks the opinion of others when it has to make a decision, it not only applicable for individuals but also for various organizations.

The content of social networks reflects opinions and feelings about nature, while the traditional content is aimed at identifying analytical topics [9], [10]. Thus, it treats with further intricate the natural language processing (NLP) problems. Due to the enhancement in the amount of information existing and the extra difficult conceptions for analysis, the interest in semantically based usage has decreased in recent years, and statistics and visualization have moved towards greater use. Like other science subjects, automatic content analysis is becoming a science that requires a lot of information.

Opinion-building programs are the main infrastructure for large-scale shared policy-making systems. This contributes to the meaning of the numerous kinds of involvements [11]. It will be assisting to identify early responders by identifying early warning systems for potential offenses [12]. Traditionally, specialized research is used to communicate structurally.

However, such data gathering is expensive because it requires the design project, and also data assortment is difficult. It is because people don't want to respond to surveys which make it invaluable and also information created in through predetermined question and answer will not able to justify the significance of the issues. Opinion mining is useful in identifying difficulties not by listening or not by enquiring, thus reflecting the truth more accurately is always challenging [13].

2. SIGNIFICANCE OF OPINION MINING AND INFORMATION EXTRACTION

People are always eager to explore what others believe or their remarks on a particular thing before taking any decision. The opinion of friends and relatives is also always preferred into account when making a decision [14], [15]. But nowadays, there is no need to consult with anyone where the internet is used by everyone because there are many online reviews that help you know if a product is good or bad. Opinion minerals play an important role here. Concepts such as opinion and emotion and evaluation, evaluation, attitude, influence, emotion, and mood are about our subjective feelings and beliefs [16], [17]. They are the center of human psychology and are the main influencers of our behaviour.

The explosion of social networks has provided extraordinary prospects for society to express their opinions openly but predicted the accurate meaning and polarity is quite challenging [18]. Despite the challenge, it is necessary to understand people's concerns and opinion with the increasing popularity of the social platforms, which is not consistently emphasized and some issues were needs to be shared quickly and unexpectedly important [19].

Our beliefs and attitudes toward reality, as well as the choices we make, are related to how others see and perceive the world. That is why our views on the world are so influential on others that it often seeks the opinion of others when we have to make a decision. But, from the applications point of view, we would like to study naturally the attitudes and feelings of people with a problem of emotion analysis on any issue of interest [20], [21]. More precisely, OA, also called mind digging, is a field that aims to extract opinions and emotions from natural language text using computational methods.

The emergence and rapid development of emotional intelligence are in line with social networks over the internet, such as comments, online-forum, blogs, and others, as for the fore most the individual in past has a massive amount of opinion in textual types. This so-called user-generated content has prompted researchers to find useful knowledge [22]. This, of course, has led to the analysis of opinions or the questioning of opinions, as these data are full of opinions [23]. It is not surprising that this information is full of opinions, because the main reason why people post on social media platforms is to express their opinions and opinions, so emotional analysis is the core of social network analysis.

Opinion-related information extraction can be defined as a small topic of computer linguistics aimed at mining public opinion from the Internet. The issue of NLP and data extraction aims to engage the writer's emotions in POS or NEG remarks by analysing multiple documents [24].

2.1. Information extraction

The mechanism of information extraction presented in the past to extract the relevance and structured data from the distributed unstructured data over the internet in various forms like the online post, news, documents, etc. According to the distribution of this information, it is largely categorized into two main groups of data as informative and opinion. The informative data aim to present the facts, subjects, events, and their relevant information; whereas opinion is purely are subjective expressions that express an individual's feelings, assessments, or emotions about a topic, event, and behaviour [25]. In this review, we will focus mainly on the words of opinion that give people POS or NEG emotions. Most of the past research on text data processing aims at information retrieval, web search, text classification, text groups, and much other mining and NLP, and also very little work has been proposed recently to process the opinions data [26]. However, opinions are so important that we want to hear from others when we have to decide by a person and in all types of sectors [27].

Increased interest in the production of opinions and emotional analysis is associated with its possible use. Meanwhile, the novel intellectual complexity presented to the research community is also important. Emotion analysis has been one of the most active areas of research in NLP since the early 2,000 s. It is also extensively used in data mining, web mining, text mining, and data retrieval. In detail, computer science encompasses management in the field of advertising, economics, political science, transportation, medical sciences, and even history [28]. This increase is because of the reality that opinions are essential to nearly every person's affairs and have a great influence on the behaviour and often seek the opinion of others to make a decision [29].

Traditionally, text categories documents are grouped by subject information. Several probable categories and definitions are depending on the user and the program for a given task [30], [31]. We tend to have a relatively small number of classes (such as "positive" or "asterisk"), unlike the emotional classification that is common to various domains and consumers. In addition, however, different classes of categorization by the subject may not be entirely related and the emotion tags commonly considered in the previous work usually indicate opposite or orderly/numerical categories. The regressive nature of the power of emotion, the degree of positivity and so on, which looks very different to categorize emotions [32].

However, finding and reviewing internet comment sites and cleaning them up remains a difficult challenge due to the proliferation of sites. Every page usually comprises a lot of text which is not easy to create in a long blog and posted in the forum. The regular reader will find it difficult to recognize relevant pages and compile and summarize their opinions. Therefore, automatic sensory analysis systems are needed. That’s why there are so many initiatives aimed at providing emotional intelligence facilities. Even several large companies have built their internal potential as well. This realistic purpose and production concerns gave a strong impetus to the study of emotional analysis [33].

2.2. Opinion mining

Mining community emotions and analysing them on Twitter is an easy manner to express public opinion, helping them make decisions in different areas. Twitter is a significant and popular platform for individuals to interact. The majority of the users sharing their views and opinions utilizing the Twitter platform nowadays [34]. It is important to study public opinion and find the reasons for the change in emotions to make important decisions. For example, a company can analyse public opinion to get users to comment on their products on Twitter. Generally, opinion mining collects information about the pros and cons of a particular subject. For this reason, users are encouraged to leave POS reviews and high ratings for the products [35]. Opinion mining is described as a sub-field of computational linguistics that intends on getting people's opinionsfrom the internet [36]. The latest development of the internet allows consumers to access blogs, videos, social networking sites, and more encourage them to contribute and express themselves through. All these platforms present a lot of important information that it desires to analyse. The OA on the other hand involves determining the subjectivity, polarity of a part of the text, such as weak POS, soft POS, strong POS, and so on [37].

The Internet has radically transformed the way individuals convey their opinions. They can now publish product reviews on their purchasing pages and have their say in online forums, discussion groups, and blogs, known as user-created content [38]. This online term refers to the latest and quantifiable resources with various practical applications. If someone wants to purchase a product as they consult relative and friends similarly, they explore the reviews and feedbacks or opinion of the past users on the various platform on the internet [39]. The company will no longer need to organize research, systematize focus groups or hire outside specialists to locate out what consumers think about their manufactured goods and contestants, as user-created content on the Internet can previously give them such related information.

However, identifying resources of opinion and supervising them online remains a complex task as there are many diverse sources and each source can contain countless opinion texts (opinions or sentimental text). Even these opinions are also embedded in online post forums and blogs [40]. Existing research has created many methods for a variety of issues of OA in the form of supervised or unsupervised methods. The supervised-based machine learning (ML) methods such as support vector machine (SVM), Naïve Bayes, and max entropy [41] is used to design mechanisms with attribute combinations to do supervised classification. The methods of unsupervised include different types of the lexicon, syntactical and semantically patterns to classify the opinion reach information [42]. Several research volumes and articles include numerous such methods and experiments. There are many algorithms utilized by researchers and scientists to get extremely optimal outcomes [43]. Several of them have their pros and cons in Table 1.

Table 1. Existing supervised ML techniques

Supervised ML Methods	Advantages	Disadvantages
Support vector machines (SVM)	Works well for problems with high dimensions, linear inseparable.	Several important constraints can perform with any certain data. However, it might not work with other information.
Naïve Bayes	Easier to use and requires less training data for better outcomes. It requires less memory to perform.	In several situations, low accuracy may occur when additional dependency occurs, and also dependents changing are difficult.
Decision trees	Utilizing the characteristics of the data it automatically classifies based on the low data constructions.	Diagonal's separation cannot be performed.
k-nearest neighbours	This is simple and utilized for categorizing multiple layers of information.	Time complexity is high and also requires high memory during the process.
Convolutional neural network (CNN)	It is effective because processing time complexity is less and memory usage is low.	High computational costs are required otherwise it will be slow.
Bi-directional LSTM	Employs traditional and future information to create the conclusions; thus the accuracy is very high.	Too many layers can cause a gradient explosion.
Long short-term memory (LSTM)	This method is utilized when the output of the process is utilized again. It builds a looping process for the execution.	The outcome is mostly based on the past observation results and results are futuristic, and it works in one direction.

2.3. Opinion or sentiment classification

Most of these studies describe the polarity of opinion in the form of POS or NEG of reviews post by users for a product. This problem is also known as document-level emotional classification. This is because documents treat them as the basic unit of information. Existing research suggests that the opinion of the document is apparent and can be applied for the classification of the individual sentences having a similar feeling. However, it is expected that all sentence propositions here will be considered in the past proposals. The activity of categorizing comments or opinions of a sentence is not always classified as a subjective classification. The received sentences are categorized into groups for expressing the opinion into POS or NEG form, which is known as sentiment classification in sentence-level [44].

2.4. Sentiment classification: document-level

Sentiment classification is a task in NLP that divides a text into groups based on predetermined characteristics (e.g., positive, neutral, and negative). Artificial intelligence is frequently used in sentiment classification to determine the emotional tone of an online mention, such as a social media post. This is used to determine the overall opinion of the document. Sentiment classification at the document level assumes that each document expresses opinions on a single entity.

The four primary stages of sentiment analysis are as follows. They are data collection, text cleaning, analysis, and output results. The significance of each sentence in the text is not taken into account. Each sentence in a text needs to be treated with varying degrees of relevance to identify its polarity. A document-level sentence categorization model based on multiple networks will be utilized to address this issue, allowing the relevance levels of sentences in documents to be automatically assessed using a variety of techniques. Most of the methods available for classifying opinion at the document level are depend on supervisory training, but there are also several unsupervised methods as we discuss in next sub-sub section.

2.4.1. Classification based on supervised learning

The classification of opinions can be structured into a learning problem governed by POS and NEG as a two-level class. Most of the study and test data used in the existing research were product reviews. This is not unexpected because of the primary assumptions for the classification. Every comment on a distinctive view page is easy to read and test because it already has a rating determined by the observer (e.g., 1-5 stars). Typically, a range of 4-5 star reviews is believed to be a highly accepted rate and classify as POS, in a similar a range of 1-2 star reviews is believed to be negative and not acceptable.

Recent studies have utilized various other attributes and methods for learning. Like the majority of ML programs, the primary task of emotion classification is to develop a collection of appropriate functions. Few Examples of potential research and practical properties are presented in [45].

In addition to classifying or predicting POS or NEG emotions, research has been conducted to predict the achieved marks of observers [46]. In this case, the rating scores are normalized as a regression issue. Another interesting area of research to be explored is the adaptation of learning data or domain, as the classification of emotion is very responsive to the field in which learning information is derived.

Classifiers are designed to use commented messages in one domain tend to perform poorly when used or analyzed on commented messages from various domains. This is because phrases and even language structures utilized in diverse domains to express opinions are completely different. To make matters worse, the identical word in one field can be POS and the similar word in another field will be NEG. For example, irregular attributes can point in the NEG direction in vehicle comments, but in the POS direction in the theatre play comments as described in [47]. So, it is essential to have an adapted design structure for various fields.

2.4.2. Classification based on unsupervised learning

It's easy to imagine that phrases and expressions which are the main pointers of the emotional or opinion classification. Therefore, it is very natural to use unsupervised learning that relies on such phrases and expressions. It classifies the phrases or sentences in the following phases:

- Phase-1: Initially it mines the needed adjectives or adverbs from the sentences. This is because research has revealed that adjectives and sentences are excellent indicators for topics and comments. However, although the separated adjective might designate subjectivity, this could be a sufficient situation for influential the direction of an opinion. The algorithm, therefore, produces two words in a row, where an individual element of the couple is considered as an "adjective/adverb" and the further is a perspective of the statement.
- Phase-2: The point is given in (1) evaluates the direction of the sentences extracted using the probability of mutual information (PMI).

$$PMI(wterm_1, wterm_2) = log_2(\frac{Pr(wterm_1 \wedge wterm_2)}{Pr(wterm_1)} Pr(wterm_2)) \quad (1)$$

Here *PMI (wterm*$_1$ ^ *wterm*$_2$*)* is the probability that *wterm*$_1$ and *wterm*$_2$ will co-occur, and if *Pr (wterm*$_1$*) Pr (wterm*$_2$*)* is statistically independent, the two terms will co-occur. The relationship between *Pr (wterm*$_1$ ^ *wterm*$_2$*)* and *Pr (wterm*$_1$*) Pr (wterm*$_2$*)* is thus a quantity of numerical reliance among them. This relationship is the log of the quantity of information it gets concerning the occurrence of a single word while it looks at the former word. The orientation of the opinion direction (OD) of a sentence is calculated utilizing its association to the word as POS to "outstanding" and the word "poor" as NEG: expression;

$$OD(\text{expression}) = PMI(\text{expression}, \text{"outstanding"}) - PMI(\text{expression}, \text{"poor"}) \quad (2)$$

Probabilities are computed through submitting search queries and aggregating numerical results from a search engine. For each search term search engines often return the number of relevant documents in a search query, which is generally considered as several hits. So, by searching for the two different words collectively and independently it can compute the probability of association of the expression using (1). utilized an operator known as "NEAR" to restrict searches to documents with ten words in any order for the search engines. So, if the number query results are returned in the form of hits count, then (2) can be modified as;

$$OD(\text{expression}) = log_2\left(\frac{hits(\text{expression NEAR("outstanding")}\ hits(\text{"poor"})}{hits(\text{expression NEAR("poor")}\ hits(\text{"outstanding"})}\right) \quad (3)$$

- Phase-3: In relation to the review, the algorithm calculates the mean OD value of all expressions in the comments and classifies the comments according to the submission, if the mean OD value is POS then only it is suggested otherwise it is not suggested.

2.4.3. Sentiment classification and phrase-level subjectivity

This section discusses the phrase level analysis to perform the sentiment classification [50]. For example, for a given phrase *p* the following two actions are executed: i) Classification through Subjectivity: It determines that *p* is a subjective speech or an intentional phrase and ii) Classification through Phrase-level sentiment: in case the *p* is subjective then it confirms that it provides POS or NEG opinion. In most programs, people need to recognize what an entity or feature is for and what it means as an opinion.

So the two activities of phrase-level classification are still extremely essential because (1) it sorts out the uncommented phrase, and (2) knowing what the sentence is talking about an object's characteristics. It assists to establish whether there are POS or NEG opinions about the topic and its characteristics.

2.4.4. Opinion lexicon creation

In research literature opinion or sentiment comments are also known as dramatic and expressions comments. Positive descriptive phrases are employed to describe the required state, and negative descriptive phrases are utilized to describe an unfavourable state. There are three main approaches based on manual, dictionary, and corpus that were investigated for compiling or gathering opinion word lists. The process of manual mechanism is usually not executed individually due to which it consumes lot of time and the process of automation mechanism utilizing dictionary and corpus have to make recurrence check which may have low accuracy. Both approaches based on dictionary and corpus are described.

a. Automation using dictionary

A simple method of this approach is based on opening a small set of keyword words and an online dictionary such as "WordNet" The scheme is to collect a small set of keywords in a specific direction first, then expand that set by exploring for synonyms and antonyms on dictionary and if a new word is discovered then is appended to the list. Upon completion of the process, manual tests are performed to correct or eliminate the mistakes. Researchers are utilizing other data from WordNet and additional techniques to create better lists. There is many lists of words of opinion have been compiled and presented [48].

b. Automation using corpus

The mechanism of corpus-based automation is the combined or co-occurring metaphors, and in the larger corpus, it is based on the seed of commentary to find other words. This approach starts with a list of racist adjectives and utilizes linguistic constraints or standards of different nouns to recognize supplementary adjectives in their words and their meanings.

Kanayama and Nasukawa [49] author extended this mechanism by introducing opinions about emotional concordance within and between sentences. Sentence congruence applies this comment to adjacent sentences. That is, the POS or NEG opinion tendency is the same, often expressed in several successive sentences. Comment changes are displayed with antonyms such as "but," "however," and other terms. Certain criteria have been proposed for determining whether a word is added to the POS or NEG dictionary.

Qiu *et al*. [50], proposed another method of extracting sentiment words in a specific field from comments using various opinion expressions. The main comment is the separation of the syntactic relationship between the comment word and the object property. They show that comments are often related to the nature of the object in some means. Therefore, comments can be identified by known properties and features which can be identified by known comments. Exclusion rules are designed based on the different relationships between comments and attribute having comments and features and to define the relationships it utilizes syntax dependency.

2.5. Deep learning in opinion mining

The mechanism of SA or opinion extraction categorized the classified data into three classes as POS, NEG, and neutral. This is because no person can interpret every comment and post posted on the website. Researchers and academics are so insistent on finding ways to accomplish this with less computational energy and period. Therefore, the wide scope of ML and text mining is considerable for SA. The fundamental methods of mining opinions are driven by the dictionary. It employs methods utilizing dictionary, corpus, or text manuals and hybrid methods that combine dictionaries and ML methods.

Yang *et al*. [51] solved the problem that the emoji in the sentiment analysis of micro-blog in helped to obtain accurate emotional meaning. In respect to the previous research, emoji are believed to be noisy emotional signals and do not focus on the underlying emotional feelings. Here, the author presented a new emoji-based semantic enhancement utilizing the CNN method term as ECNN. Therefore, it is able to determine through subject, sentiment, and polarity in a blog environment. In this regard, the standard of semantic combination computation of vector illustration, using many common emojis to construct emotional space, emotion vectors, and word vectors are clearer. People often use these emojis to convey their opinions because they are simple to recognize and associate and able to participate as an important function in mining opinions.
a. Deep learning

The common constitution of an artificial neural network (ANN) was motivated by the activity of the human brain mechanism. It points to a computing system consisting of many simple interconnected processes designed to explain difficulties by intensive study of a huge number of the data training process. The network takes some input and acts as an association of nodes with connections and weights and is placed in layers. Grekousis [52] describe ANN as the association of the nodes and different type of layer to determine the structural design. Typically, the mechanism lies in a hidden layer between input and output layers. The complexity of ANN design is structured according to the training data, hidden layers, and associated nodes. Mostly if the datasets are complex and they might have several additional layers.

The conversion of the input to the output is carried out by the deep neural network (DNN); it has discovered the accurate arithmetic method to convert the input to the output. These systems have been studied to find appropriate emotions in such a way that they are likely to achieve accurate results because they have different methods. As examines the efficiency of deep learning (DL) by analysing the customer opinions of hotels, it also demonstrated a method for mining for the agriculture datasets and suggest a hybrid semantic method.

The DL mechanisms which are related to the ML are more accurate to the ANN multilayer class. The peculiarity of the DL method is that they have diverse altitudes of demonstration and concept to assist and understand the data presented by Deng and Yu [53]. Colbert and Weston [54] describes the usage of DL mechanisms in various domains like image and text processing. The past studies present a lot of works having the mechanism of DL and NN such as CNN, recurrent neural network (RNN), LSTM, autoencoder (AE), and deep belief network (DBN). Samira *et al.* [55] present a detailed survey on the prospect of the DL algorithm and its application. DL methods for sentiment classification show in Table 2.

Table 2. DL methods for sentiment classification

S.No.	Author	Neural networks model	Representative works
1	Moraes *et al.* [25]	Artificial neural network (ANN)	It conducts an empirical comparison of document-level sentiment classification between SVM and ANN, which shows that in most cases, ANN produces results that compete with SVM.
2	Tan *et al*. [44]	Paragraph vector	To overcome the weakness of the BoW, it suggested a vector of the paragraph, which is an unsupervised learning method that can study the representation of vector and changeable text context.
3	Kong *et al.* [1]	Stacked denoising autoencoder (SDA)	They proposed a DL system based on stacked noise reduction auto encoders, with rare correction devices that can perform unsupervised text extraction using labeled and unlinked data. These attributes are very conducive to the domain adaptation of sentiment classifiers.
4	Grekousis [52]	Denoising autoencoder (DAE)	Especially the model examines the problematic text format by attenuating the loss method to the Bregman Divergence difference in the autoencoder and obtaining the loss function that differs from the labelled data.
5	Abdia *et al.* [4]	BoW-CNN and Seq-CNN	It proposed a CNN version called BoW-CNN, which uses word adaptation in the convection layer. It also developed a novel model known as "Seq-CNN" that combines a hot vector of several words to store consistent data of words.
6	Yang *et al.* [51]	CNN, LSTM and GRU	First, it will learn the form of the proposal from CNN or LSTM from the proposal. GRU is then used to classify emotions to encode the semantics of phrases and their unique relationships in document illustrations.
7	Morinaga *et al.* [22]	UPNN utilizing CNN	It uses representations and classification to categorize reviews. This opinion can obtain important universal information, such as the specific needs of the customer and the general nature of the elements that can offer enhanced visualization.
8	Collobert *et al.* [54]	UPA based on LSTM	In the first section, LSTM is used to study document presentations. In the second section, a deep memory system having multiple computational layers is utilized to predict the validation level of each document.
9	Rajesh *et al.* [56]	LSTM	The long text format offers a cached LSTM model for general semantic information. Memory in the model is divided into several groups with different memory speeds.
10	Chen *et al.* [5]	GRU-based sequence encoder	This model has two levels of attention mechanics: one at the terms level and another level is at the phrase level. It pays attention to specific terms or phrases when creating a document representation.
11	Xia *et al.* [33]	Memory Network	Contrast memory networks are recommended to classify feelings between domains in a transition environment, where the source domain and the target domain information are modelled together. Two systems have been created for opinion classification and the domain classification.

b. Neural networks

DL has become a major ML technique that provides the most up-to-date solutions for many mining applications. It is utilized in various computer visualization and recognition application applying NLP, the use of DL for emotion analysis has also become increasingly popular recently. It is used in ANN implementation for training assignments using multilayer networks. It can take even more power to learn NNs that used to be seen as just one or two layers and a small quantity of information. Inspired by the structure of the biological brain, NN contains information that works systematically. It can be trained to functions such as classification by regulating the weight of associations among neurons which is similar to the biological brain learning process.

Depending on the network topology, NN can usually categorize into "feed forward NN" and "recursive or recursive NN", which are diverse and matched. Figure 1 shows a simple instance consisting of three layers as L_1, L_2, and L_3a for a feed forward NN.

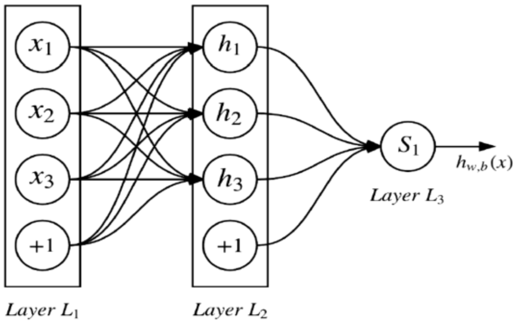

Figure 1. Feed forward neural network

The input layer "L_1" corresponding to an input vector having "x_1, x_2, x_3, . . x_n" values. The middle layer is the hidden layer as "L_2" in which execution results are not seen in-network, and the last layer is the output layer as "L_3" it provides execution output value vector as "s_1".The circles at "L_1" represent the elements of the input vector while the circles at "L_2" or "L_3" represent neurons, which are the basic computational elements of a NN. As in Figure 1, the NN changes weights depends on the learning patterns, and later in the learning development, it assumes the multipart structure of the proposition form $h_{w,b}(x)$, which corresponds to the information. The CNN is a supervised multilayer feed-forward NN. It consists of three phases named: "Convolution", "Non-linearity" and "pooling".

- Convolution: At this stage, operations based on convolutional mathematics are used. This procedureaspires to remove properties from the input and then transfer into layer after results generated.
- Non-linearity: The purpose of this phase is to combine nonlinear characteristics with the grid employing nonlinear operations.
- Pooling: The most important goal of this phase is to reduce the size of the mapping with utilizing a function called maximum or average pooling.

3. EXPERIMENTAL RESULTS

This section explains how supervised learning techniques like logistic regression, Naive Bayes, and support vector machine were used to get experimental findings from a twitter dataset [57], [58]. The confusion matrix for each logistic regression Naive bayes, support vector machine network is presented in Tables 3-5 the accuracy of the performance matrix is computed. These comparisons show that support vector machine has the best accuracy. The network can therefore be reliably used for a twitter dataset in real-time applications. Confusion matrices are generated based on the subsequent conditions.

- True positive (TP): The data accuracy values were positive and were predicted positive.
- False positive (FP): The data accuracy values were actually negative but falsely predicted as positive.
- False negative (FN): The data accuracy values were positive but falsely predicted as negative.

Table 3. Confusion matrix of logistic regression

	Pos.	Neg.	Total
Pos.	8839	90	8929
Neg.	448	212	660
Total	9287	302	

Table 4. Confusion matrix of Naive Bayes

	Pos.	Neg.	Total
Pos	8921	1	8922
Neg	580	87	667
Total	9501	82	

Table 5. Confusion matrix of support vector machine

	Pos.	Neg.	Total
Pos.	8893	29	8922
Neg.	315	352	667
Total	9208	381	

3.1. ROC curve

A receiver operating characteristic curve which is also call as receiver operating characteristic (ROC) curve, depicts how well a classification model works at various levels of categorization. Two parameters are shown on this curve are: The result is shown in Figures 2-4 with the optimal number of classes. As class values increase, causing the class to overlap, their corresponding area under (AUC) the ROC curve values decrease considerably. Think about integral calculus while calculating the AUC; it measures the full two-dimensional region beneath the entire ROC curve from (0,0) to (1,1). From this perspective, scenarios in which only low to moderate AUC evaluations are observed for a given ground-truth solution, cannot be properly recovered despite support vector machine algorithms.

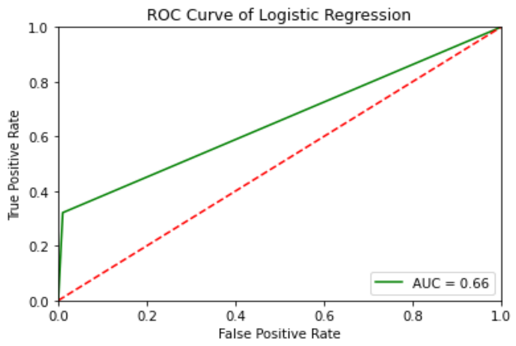

Figure 2. ROC curve for TF/IDF vectorizer of logistic regression

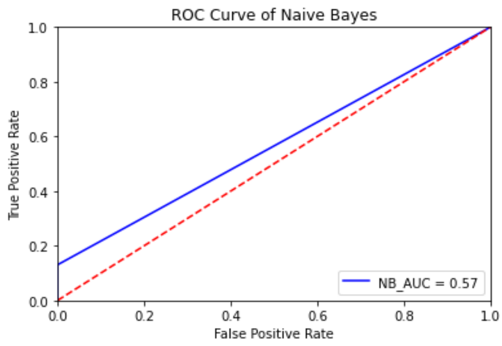

Figure 3. ROC Curve for TF/IDF vectorizer of Naive Bayes

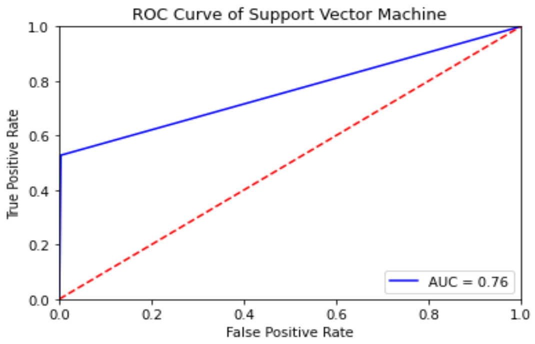

Figure 4. ROC curve for TF/IDF vectorizer of support vector machine

As shown in Figures 2-4 as ROC Curve for TF/IDF vectorizer of logistic regression, Naive Bayes and support vector machine are viewed. Here the true positive rate and the false positive rate is evaluated. As shown in Figure 5 the best recall belongs to support vector machine of 96.57%. This algorithm returned most of the relevant results compared to logistic regression and naïve bayes. The f-measure is also more for support vector machine with 98.1%. The accuracy is best for support vector machine with a percentage of 96.41% compared to logistic regression and Naive Bayes.

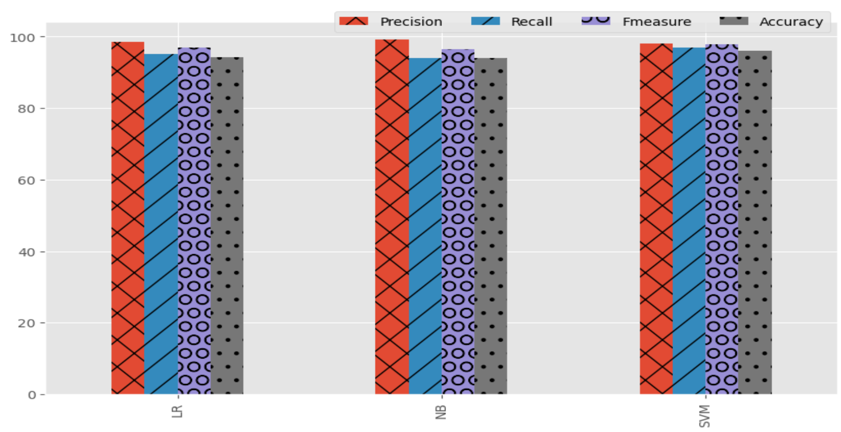

Figure 5. Performance of logistic regression, Naive Bayes and support vector machine

4. FUTURE RESEARCH PROSPECTS

There are problems in regarding supervised techniques for semantic analysis of opinion mining for the extracted information. There have been problems and difficulties in the in-depth study in DL for the opinion mining area. There has been significant progress in the field of the opinion mining sector. But there are still many challenges in this regard to that need to be considered. It is not always essential that the use of bad words leads to bad or bad results; however humorous words and jokes are also utilized by various to express opinions. Therefore, the sentence may or may not be severe depending on the circumstances. The result may not be accurate when given a complex review that mixes several things, despite one line of sentence reviews. These types work well for training and knowledge testing, but there may be less accurate in real-world knowledge. Individuals express their senses in diverse manners when objects change in different phases. Spammers often post false or spam comments to influence product reviews for personal gain. It is difficult to clarify and minimize the correct view in comparison sentences.

Current research is focussing on:

- Enhancing the accurateness of the methods for determining opinion.
- Reduce the manpower required to analyse the substance.
- SA through the lexicon or corpus terms with certain emotion to classify emotions.
- Identify policy-opinion materials for evaluation.
- Visualization association of bipolar opinion.

5. CONCLUSION

The mining industry is rapidly changing its opinion mining. Opinion mining is quickly changing the business. Sentiment analysis showed that it is not just a single problem, but a multifaceted problem with many interrelated sub problems. Researchers can use relationships to develop more reliable and accurate solutions for analysing relationships, and practitioners can see what is needed to build a system of emotion analysis. In this review, we have tried to present an existing assessment and inform of the sensitivity analysis, which is typically made with a social network. It has been seen in the past that different literature and research has been done in this area and now that we have worked on it, it is now clearer that emotion analysis is a deeper topic and useful for market growth. The uses of the DL study of emotion analysis have recently grown to be a well-liked exploring area. It also presented their in-depth analysis mechanisms and their use in emotion analysis. The best accuracy is for support vector machine with a percentage of 96.41% Compared to logistic regression and naïve bayes. Several of these DL methods have revealed the most modern outcomes for different emotional analysis issues. It believes that the development of DL study and practice make it additional interesting explorations of DL in the coming future prospects.

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