Textual Sentiment Analysis using Machine Learning and NLP: A Review

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One of the most prominent parts of opinion mining is sentiment analysis that is used to extract emotion from textual features. Through this process, it can be determined whether a piece of writing is positive, negative, or neutral. This paper presents a review on the sentiment analysis task using textual data. A sentiment analysis system for text combines Natural Language Processing (NLP) and Machine Learning Techniques to assign weighted sentiment scores to the entities, topics, themes, and categories within a sentence or phrase. One of the prominent parts of opinion mining is depression detection. Nowadays, a significant section of society is affected by depression due to mental stress. So, it is also a considerable concern. There may be several reasons for depression, especially in adults. Different people have different symptoms, and its identification is a significant challenge. Most people feel shy to accept that they suffer from depression, while some people are unaware of their depressed mental health. The objective of this paper is to analyze recently developed frameworks for the diagnosis of sentiment and depression level of an individual. This paper directs towards creating a single framework in the future for depression and sentiment analysis.

Keywords: Sentiment Analysis, Natural Language Processing, Depression Detection, Emotion recognition, Machine Learning.

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1 Introduction

The electronic age is characterized by increasing numbers of information, which are also known as the information society. The volume of social media content users create is growing rapidly, driven by the current generation of web applications, almost unlimited connectivity, and an insatiable desire for information-sharing, especially among younger generations. People using the web are constantly invited to share their thoughts and preferences with the rest of the world, resulting in an explosion of opinion blogs, product reviews and services, and almost anything comment. The whole kinds of social media content are increasingly recognized as a value-added data source for several technology areas [1].

Governments and commercial organizations have struggled to determine their target groups and audiences' views for ages. The people are now publishing their views voluntarily for everybody on the World Wide Web for the first time. This social web provides almost immediate product feedback, inventories, policy, etcetera. A large amount of the desired data is currently available, which was hard to obtain in the past. This strongly opposed the conventional surveys and questionnaires often rejected by participants, which resulted in sub-optimal information without any personal motive. This mainly refers to product reports that have indicated that consumer behavior is impaired. In addition, the information supplied by people on the web is more trustworthy than the vendor's information. Every person is a potential customer from a producer point of view [2].

In reality, web-based views have become a platform that businesses use, much like conventional words of mouth. Therefore, knowing their preferences and dislikes might have a tremendous value in developing and managing new products. In addition, knowing that feedback in product reviews, for example, connects with information supplied by businesses helps marketers take advantage of these reviews and boost sales. Besides this conventional model for suppliers and customers, sentiment analysis is often crucial for many other areas of the economy, such as capital markets [3].

The paper is organized as: Section 2 represents the overview of opinion mining in sentiment analysis work. Section 3 introduces a brief overview of aspect-level sentiment analysis. Section 4 is dedicated to giving a brief description of depression detection from textual features. Section 5 provides a short literature review. Finally, in section 6, the paper represents the conclusion of this review and gives an insight for future research work.

2 Overview of Opinion Mining

The main objective of Association Rule mining is to determine a group's views on a subject. This research field, called opinion mining, sentiment analysis or studies opinion, analysis of subjectivity, feeling, judgment, evaluation, and emotional phenomena, attitude [4]. There is also a very high use of the term' sentiment analysis.' It comes from the domain of the production of natural languages and is directed at evaluating the feeling of the text. The word subjectivity analysis is often considered both an analysis of opinion and feelings, and related activities, and a subtask for an analysis of opinion and feelings. However, all these terms are the same area of study and can be used for slightly different activities or angles.

An opinion It's the reverse of reality in this context. These words are sometimes referred to simply as views or feelings for simple comparison, but theoretically, they are not the same. A decision or conviction not based on certainty or proof may be considered an opinion. Declarations voicing a viewpoint are often arbitrary, while truthful representations are impartial. Feelings in this respect are orthogonal, and they are closely linked to mood and emotion, used to offer an assessment of the matter under dispute. Due to this orthogonality, a sentence can fall into four quadrants. It can be emotional or factual, with or without emotion.

Fig. 1. Different Forms of Opinion Mining

E.g., in "Others, it seems a blue and black dress, but for me, it is a gold-white dress," people may have different views on the color of a given dress, but they don't show any emotion. In comparison, it is very logical, and without emotion, that the declaration "Some people were looking at the uniform and saw a dress of black and blue, others were convinced they were white with gold." Subjective and factual arguments can express emotions. For instance, "The most beautiful is the blue and black dress" is a descriptive declaration of emotion, whereas "My favorite dress is sold out."

3 Aspect-Level Sentiment Analysis

Generally speaking, three production phases in the study of emotions at the aspect level can be distinguished: recognition, grouping, and aggregation. Although not each approach uses all three measures or in this exact order, it raises fundamental problems for the study of emotion at the aspect level. The first step is to define feeling-objective pairs in the text. The next task is to select the teams of emotions [5]. The emotion conveyed is categorized into various positive and negative sentiment values. The goal is also often identified by predefined attributes. The goal is also often identified by predefined attributes. Ultimately, feeling values are added to give a concise overview of each aspect. The presentation relies on the application's particular needs. There are additional concerns in addition to these core elements of aspect-level analysis: flexibility, robustness, and speed. Most user-generated content needs to be robust to deal with informal writing styles [6]. Many people make mistakes, like language, emoticons, and other constructions, which are used to express those emotions, in the spelling and grammar of many. The willingness to interact with many realms is versatility. An application might be effective on a specific domain but very bad on a related domain or even mediocre across all disciplines. Finally, due to Web allergy, a feedback analysis solution at the aspect level is ideally accessible with a web interface that underlines the requirement of very high speeds [7][8].

The object of aspect analysis, on the other hand, is to locate sentimental pairs in a specific text (This could stretch from phrases or small text units to full businesses that contain several documents). The entire feeling would usually refer to the entity within the aspect-level analysis. In contrast, the aspect-level analysis would refer to the feeling relevant to the facets of the entity being debated. This encourages more research, which takes advantage of the details presented by the textual examination [9][10].

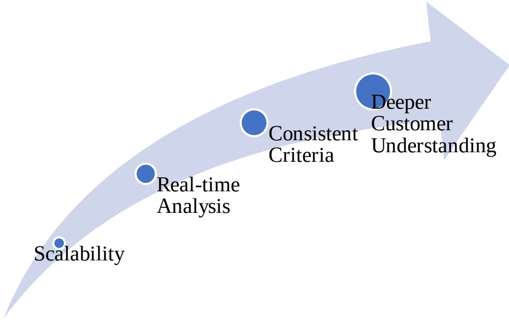

Fig. 2. Advantages of Aspect Level

4 Depression Detection from Textual Features

Throughout the world, many people suffer from depression. Depression is one of the causes of disability in humans. Physicians can't diagnose a depressed person by physical checkups. A Physician can't approach the depressed at the beginning of the stage of depression; this can lead to worsening the condition of the patient. During the depression, when none is aware of the depression, the patient tries to express his condition with social media's support and somehow reveals his feelings. So, for the patient with depression, social media becomes the main platform or source of collecting information about the physical and mental illness of these persons [11]. The accurate diagnosis of depression cannot be made because there are no available investigative techniques; the methods of physician expertise diagnose it. With the cooperation of the patient with the physician, it is hazardous with a variety of objective preconceptions [12][13]. Mood swings and depression are some psychological muddlesthat can lead to the ailment and limit performance.

In many cases, severe depression can even lead to suicide. WHO has reported that [14] over 350 million public suffer from depression globally. Two-thirds of suicides every year are mainly because of depression [15].

The suicidal death of the depressed person is 30 times more than the people who have no such disorders [16]. It is also found that two patients' symptoms are not always the same; they have different patterns of behaviors. The psychologist diagnoses the patient of depression people with frequent counseling by referencing the general employed investigative and Statistical approaches of psychological muddle criterion. Nowadays, people share and post their thoughts and feelings on social media. They also share their private status and psychological disorders on social media sites what's up to Twitter and Facebook. The patient usually uploads their routine life on social media sites, and it can be used to trace their routine life as well asthe psychological conditions of the patient. For the investigation of psychological healthiness, many approaches by researchers have been developed with the utilization of social media [17].

By employing lexicon-based methods, researchers can identify developed psychological disorders, and it is a natural language processing method and latent Dirichlet topic method. The new research in this field for the sake of improvement of the performance of the model by applying vector space illustrations and RNN (recurrent neural network) layers with consideration [18] applied for identifying and clarifying comments explaining the predicament. Research executes a model that produces aggressive and severe consequences for detecting psychological disorders of the patient using social media. Some psychological emotions and societal features of a depressed person develop connections in societal communications. Still, in online communication, there are occurrences of gloom expression [19] done by depressed one in online communities, on the online platform the patient tries to find self-respect by associating and communicating. It often gives psychological indications [20]-[24], the usage of social media, and the affectation of social media on the patient. Meditation is a tool employed by Psychiatrists to check the response where they treat reactive and repetitive agony [25]; the physician tries to trace a person's anxiety occurrences and their growth of psychological disorder [26], the depressed person searches for the online communities that provide a platform to the user to reflect their mental reactions on incidents that are awful, and that comprises the social media to draw attention. Furthermore, the contribution of the societal impact is a lot in making a sensible association among anxiety anda psychological disorder; it also affects the performance becomes leading parts of psychological disorder aspects [27]. With all these observations, it is concluded that the depressed person is also susceptible to social media, as it is prospective for these patients to express themselves on online networks.

5 Related Works

Yang et al. [1] proposed a lexicon-based SLCABG model that merged Deep Learning (DL) algorithm Convolutional Neural Network (CNN) with sequence processing model Bidirectional Gated Recurrent Unit (BiGRU). In terms of methodology, the SLCABG model presents the advantages of DL architecture and sentiment lexicon to address the inadequacies of the present reasonable inspection model for product evaluations.

Xu et al. [2] proposed a big data technique. Using a NN algorithm, the technique consolidated topic-related information into textual form. A context-aware vector is suggested for the weight computation for every term, as well as the attention mechanism was introduced into a NN model. Additionally, the training data is obtained using the sensible dictionary tagging process, which improves the model's acceptability.

Meyyappan et al. [3] proposed a framework based on common sense knowledge created to ontology of Oman touristry, based on ConceptNet.

Xu et al. [4] offered an enhanced method for word representation which unites the sentiment information contribution into the conventional algorithm of TF-IDF and produces the vectors of the weighted word. The Vectors of the weighted word are input into the BiLSTM (bidirectional long short-term memory) for capturing the contextual info efficiently, and the vector's comments are represented better. The feedforward neural network classifier gets the comment sensible tendency. In the same condition, the offered sensible inspection of the method is compared with the sensible inspection methodologies of CNN, LSTM, NB, and RNN. The practical outcome shows the offered sensible inspection methods have high precision, F1 score, and recall. The methodology was demonstrated to be efficient with more efficiency on comments.

Iqbal et al. [5] offered a united framework which bridges the gap between approaches of ML and lexicon-based for achieving better scalability and accuracy. To fix the scalability problem that comes with growing the feature-set, a novel genetic algorithm (GA) based on the feature reduction technique is offered.

Wongkar et al. [6] structured a model for data inspection of Twitter, which was guided in 2019 by candidates of the Republic of Indonesia presidential. A similar methodology is used for helping the classification of classes or sentimental level of society and achieved 75.58% efficiency value.

Lam et al. [12] used machine learning (ML) to concentrate on automated ways for diagnosing depression only by clinic observation and therapies. The models were trained using multi-modal data for such aim. With the exception of effective ML prospects such as context-aware evaluation to technical specifications and end-to-end Deep NN in diagnosis of mental illness using DAIC Distress Analysis Interview Corpus, a suggestion has been created to add a new methodology which integrates the operation of data augmentation based upon topic modeling using transformer but also deep 1D CNN diagnosis of anxiety. The simulation results show that the provided approach is effective in training multi-modal deep learning techniques.

Trotzek et al. [13] suggested utilizing ML algorithms to predict the early stages of depression based on social media postings. A CNN is used to compare and contrast classifications based on user-level linguistic information and word embeddings. The original score is compared to a measure that has been considerably changed. State-of-the-art findings in a recent early diagnosis challenge are attained by combining both techniques. Furthermore, the newly popular ERDE performs well enough in initial detection techniques, and it investigates its flaws in the establishment of shared duties.

Finally, using the task description (a brief info about task), an updated word embedding has been trained using a large corpus similar domain, which was then assessed using the task description. For train the dataset and assess effectiveness, Tadesse et al. [14] used Natural Language Processing (NLP) methods as well as ML algorithms. This strategy follows a vocabulary of more often used phrases amid depression reasons. According to the findings, the recommended strategy may significantly improve model performance as well aas accuracy. The Support Vector Machine (SVM) categorized a bigram or digram among the top single characteristics for diagnosing mental illness with 80 percent accuracy as well as 0.80 F1 ratings. The Multilayer Perceptron (MLP) classifier proudly displays the effectiveness as well as collective power characteristics (LIWC+LDA+bigram), this leads to the better implementation for identifying depression, having point 91 percent accuracy but also 0.93 F1 ratings. Utilizing publicly accessible data, Syarif et al. [15] created a corpus of Self-proclaimed mental illness discovered on online sites such as Twitter. Inside the research proposal, the computational linguistic (Computational analysis) procedure is used to estimate the depression rate in digital networking sites using linguistic as well as emotional aspects. Suggesting the features of SenticNet's 4 emotional dimensions, following are state of mind like thought/feeling at present, self-reference, as well as mental illness word count. The findings are shown via the application of a rule-based framework for assessing the degree of depression on the basis of language/dialect.

Table 1 gives the comparative study of various methods for sentiment analysis. Some of the machine learning approach used for sentiment analysis in different domains are presented in fig 3. This represents the state-of-art comparison of techniques and from this figure it can be observed that deep learning models such as CNN, BiLSTM performs better as compared to lexicon based approach.

Table 1. Comparative Review on Sentiment Analysis

Ref	Description	Results	Drawbacks
[1]	Convolutional Neural Network (CNN) and attention-based Bidirectional Gated Recurrent Unit (BiGRU) based product review sentiment analysis.	~93% accuracy	It was observed that non-weighted words cause issue in correct classification.
[2]	Word weight vector was evaluated as analysis of context and further feed to neural network for further classification.	~91% precision	Binary classification and sentiment data dictionary is not considered.
[3]	Domain-specific ontology combined feature extraction, lexicon-based approach, and conceptual semantic	~83% Precision	Lexicons are not well focusedfor opinion mining.

	sentiment analysis to determine the sentiment analysis of tweets about Oman tourism.		
[4]	Weighted word vectors with BiLSTM for sentiment analysis	~91% precision	BiLSTM consumes a long time in the training model.
[5]	Lexicon-based and machine learning with genetic algorithm optimization for domains such as terrorism, global conflicts, and social issues.	~90% Accuracy	This was limited to single criminal domain and evaluated only accuracy.
[6]	Twitter data sentiment analysis using Naïve Bayes.	~76% accuracy	In each sentence word frequency was evaluated that results in less accuracy as frequency cannot determine the sentiment correctly..
[29]	Deep Neural Network model with Feature Adaptive Transformation & Combination strategy.	Accuracy=77%	The performance rate is quite low.

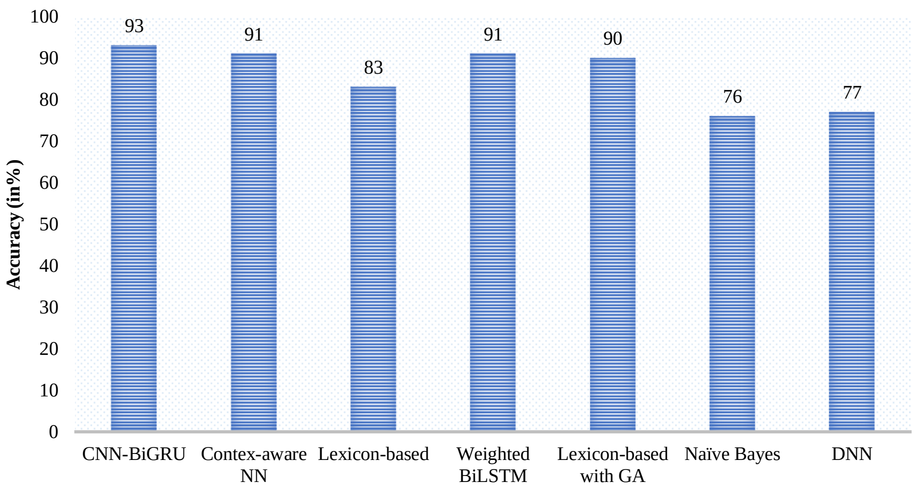

Fig. 3. Comparative state-of-art of sentiment analysis ML tools

6 Conclusion

Out of all communication mediums, the textual medium is one of the most privileging mediums nowadays. People are expressing their sentiments by sharing their opinion. Over most of the applications, people express their feelings by sharing reviews, and people trust any application by analyzing reviews, whether it is about any product, movie, application, news, etc. Whether social media or e-commerce websites, a trust level is established by analyzing reviews. Similarly, textual analysis is also effective in the depression detection process as depression is a severe mental illness that needs to be monitored for good individual or social growth. The current diagnosis system requires a trained analyst or psychologist to observe the scale of depression levels. The accuracy of the analysis depends on the expertise of the analyst or doctor. Generally, doctors analyze the depression level by questionnaire or body language situation handling abilities of an individual. But, sometimes, in manual analysis, the wrong prediction can be performed. Another drawback of automatic diagnosis is that there is always a need fora psychologist for analysis. Thus, the above two main domains, sentiment analysis, and depression raise the need foran automatic depression detection tool or framework that can diagnose sentiment or mental health of an individual without any expert. Many research works were conducted with facial expression, textual, and audio emotions using the machine learning approach. But these system results in bias result and are not that much accurate. So, this paper focus on surveying different approaches along with their limitations. From result analysis, it can be seen that highest accuracy was achieved by deep learning models such as CNN and BiLSTM. So, for future research work it can be suggested that deep learning models can be adopted for sentiment analysis instead of lexicon-based approach as the sentiment analysis field can be effective in many domains review analysis, mental health diagnosis, product analysis, social trend analysis, etc.

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