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Review Article

Depression Sentiment Analysis using Machine Learning Techniques: A Review

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Abstract:

Depression is one of the habitual psychological well-being diseases and a significant number of depressed individuals end their lives. People suffering from depression don't ask for help from psychological doctors due to hesitation or unawareness about depression that causes a delay in diagnosis and treatment. A lot of people share their opinions and emotions on social networking sites. Several studies of social networking site posts related to depression rely upon Facebook, Twitter, Blogs, and other social networks because they help in recording behavioral attributes which are related to a person's thinking, socialization, communication, etc. Datasets from various social networking sites are useful for depression sentiment analysis. Various machine learning and deep learning techniques like Naïve Bayes, maximum entropy, Support Vector Machine (SVM), and Decision Tree classifiers neural networks, deep neural networks, recurrent neural networks etc. have been used for depression detection. This paper presents a review on sentiment analysis performed on social media platforms for detection of depression The datasets utilized are also discussed. A comparative analysis of existing work in the area of depression detection is provided to get a clear understanding of the techniques used. Finally, challenges and future work which can be done in the field of depression detection is also discussed.

1. Introduction

The World Health Organization (WHO) defines depression as a familiar psychological ailment, indicated by unhappiness, no interest, feelings of regret or low self-confidence, troubled sleep or hunger, and less attentiveness [1]. By a report provided by the WHO in 2012, above 350 million persons were affected by depression worldwide. It was revealed that the possibility for a person to face a crucial incident of depression in a year is 3-5 percent for men and 8-10 percent for women [2]. In the worst-case scenario, it can cause suicide. Research proves that around 1 million people having depression commit suicide yearly [3].
Depression could be cured efficiently if depressed individuals can provide cooperation to the doctors for proper treatment. However, not more than half of the patients get good treatments globally. Moreover, the scenarios of depression differ in every nation [4, 5]. As represented in table 1, the nation with the greatest existence of depression globally is Afghanistan that consists of the lowest medical services and the least well-being treatment level due to the civil war. Contrary, Switzerland, and India have the top treatment for mental well-being consisting of more than 40 psychiatrists for every 100,000 individuals. Even for the nations which have good medical safety, the stress of the disorder from depression is decreased by 10–30 percent only.

Table 1. *Existence of depression in nations [3].*

Country	Existence in percentage	Psychiatrists per 100,000 people
Afghanistan	22.05	0.16
Switzerland	6.1	41.4
United States	4.4	7.8
China	3	1.5
India	7.5	0.3

Depression is among the major well-known mental well-being ailments and a serious problem for medical and mental well-being professionals. Proper diagnosis can be useful in its detection that could help predict and prevent depression altogether. So there is a requirement for systems that could help in dealing with these problems and help the patient. Therefore, analyzing the feeling of depression is an effective way of detecting depression levels in people and providing treatment accordingly. Depression, also known as the medical disorder is often identified as mood swings, unhappiness which influences how people think and manage routine tasks [6]. Although depression and other psychological disorders might cause separation from society and separation, yet, it was experimental that SM is utilized more and more by depressed people for associating with other people, sharing their life happenings, and helping one another [7,8,9]. Social Networking Sites (SNS) is a web group in which individuals could create a network globally, regardless of demographic and geographical dissimilarities; and can convey sentiments and opinions with one another [10-12]. Social media describes, on the whole, the internet and mobile platforms which permit people to associate with other people inside a virtual network [13] (like Facebook, Twitter, Instagram, Snapchat, and LinkedIn). On such platforms, people can communicate, co-design, or interchange different kinds of digital content like data, texts, pictures, videos [14]. Modern analysis in various surveys has focused on confirming social media opinions that increase overall confidence in information values that help monitor problems and trends that occur well. Twitter is a social networking site that allows users to show news, data, and private updates to other people in tweets or statements of characters up to 140 or fewer [11]. Opinion mining is the procedure of deciding the sentimental sound beyond a sequence of words, utilized for getting knowledge about the attitudes, opinions, and sentiments displayed in a message. It is a method of assessing written or spoken language to analyze the expression being positive, negative, and neutral. The ability to extract emotional understanding from social information is a widely used method by organizations around the world.

Prenatal depression (PD) means depression after pregnancy (prenatal depression) or postpartum (postpartum depression) or miscarriage. The signs of antenatal depression are similar to others[15]. The 5th edition of the Psychiatric Diagnostic and Statistical Manual was released by the American Psychiatric Association (APA) in May 2013 [16]. The identification advances from four weeks post-delivery to gestation. PD, menopause problem, and premenstrual disorder are known as the 3 major reasons for mental problems in females. Additionally, perinatal females in rural locations might not have expert doctors. By implementing the National Second-Child Plan and accelerated progress of perinatal women, skilled techniques are needed to investigate perinatal depression. Various survey organizations have identified that screening techniques for perinatal depression need little human interference and a greater extent of automatic techniques [17]. Probability plot designs for learning certain gene regulation procedures were given [18] that showed better-estimated outcomes for testing.

This article discusses the application of various techniques like Inverse Boosting Pruning Trees (IBPT), CNN (Convolutional Neural Network), Support Vector Machine (SVM), Natural Language Processing (NLP), multinomial naïve Bayes (NB, etc. for depression detection along with the future enhancements which could be done in these methods. Datasets commonly used for depression analysis from social media data are also discussed. The rest of the paper arrangement is as follows. Section 2 surveys related work on depression analysis using different machine learning and deep learning methods. The existing datasets commonly used in the analysis of depression are also discussed. Section 3 provides a comparative analysis and at the end the review is concluded with the analysis of existing methods.

2. Related Work

2.1 Datasets used in Depression Analysis

It refers to the information sources which focus on messages from different social media platforms which can tell about the user's mood and help in the detection of depression. Different social networking sites have variations in quantitative facts like the length of messages; vocabulary utilized etc which are considered for processing. There are variations in people world-wide like socio-economic attributes, languages, concepts about mental well-being and hence, the reasons for writing posts are different. Hence, studying the social networking site's datasets is important. Many earlier studies of depression-related social networking site posts are dependent on Facebook, Twitter, Blogs, and other content. There are few differences among these platforms and hence, the datasets are different. These datasets provide a great means for recording social aspects which are related to a person’s thoughts, feelings, socialization, conversations, and interests as described below:

Twitter

Twitter is one of the most popular social networking sites with a large amount of accessible textual content [116]. Almost every action on Twitter is public by default, and users send their text to someone who intends to listen. This openness provides a great source of information – around 90 million tweets daily and the researchers are rapid in capitalizing on every tweet. The Twitter database is gathered for the recognition of depression. The findings from the analysis of tweets from depressed user accounts are that they are less likely to tweet, possibly posted late night tweets, more likely first-person pronouns, less likely that third-person pronouns are used, less likely to have followers.

CLEF eRisk 2017

The CLEF eRisk datasets contain training consist of people's posts taken out from Reddit. The datasets are split into ten chunks each, arranged sequentially. Every chunk depicts an order of writings for a particular user for a particular period. The sequential features of the user writings at the time of processing both training and test information are used. At the time of processing the training information, the user posting frequency is calculated. At the time of processing the test information, single and multiple chunk estimations are taken into consideration,

Facebook (FB)

FB is the greatest possible origin of information as it is utilized by approximately 1.13 billion people each day, and is a major platform for assisting mental health campaigns and enrolling survey members in mental well-being research [1]. Research has been done on FB users posts to access their mental phase. Many findings have been reported like on rainy days people don't generally post good and there is an influence of friend's status on the behavior of an individual. It has been observed in previous studies that the depressed people are less likely to create posts or share any media, to involve with other people, to get any comments from friends and they don't utilize the first person, and raise queries.

Blogs and Journals

Blogs are used by people as personal notebooks, and they use them as a means of displaying and sharing everyday events [15]. Users can explain posts such as metadata with labels regarding their feelings. Livejournal.com was among the initial which provided such self-explanation characteristics to users and it was utilized in various researches. (SemEval 2007 dataset. A depression dataset was created from 38000 posts extracted from sub-communities for depression, self-harm, bereavement, etc., and a control set of 23000 posts from other, less dire sub-communities.

2.2 Literature Review:

The utilization of social networking sites has grown in the last decades, as well as latest studies analyzed that 90 percent of web teenagers and youngsters in the United States utilize social networking websites [19]. Among the most common website is Twitter having nineteen percent of web American youngsters utilizing such sites [19]. 35% of web end-users between the age-group of 18 and 29 utilize Twitter, even; American adults titled it the "dominant social networking site" in a 2013 market analysis study [20,21]. Moreover, recent information from a 2014 review from the Pew Research Centre noticed that 23 percent of networked youngsters presently utilize Twitter, which has grown 5 percent since 2013 [22]. Twitter is a micro-blogging network in which end-users provide brief updates that are shorter than 140 words. Such "Tweets" are then observed by a series of "followers" who selects to accompany the customer's social media account [23]. The threat elements of depression are diverse as well as complicated. Various surveys emphasize psycho-social components like persona, life happenings, social assistance, as well as social relations [24,25]. The clinical basis for depression is mostly based on the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) issued by the American Psychiatric Association (APA) [26]. The detection of depression is to compute the frame of mind of the patients, in which frame of mind is firmly connected to patients' actions as well as other atmospheric elements.

In Computer Science the survey for automated depression investigation has begun recently. There exist some works which examine various elements as well as information sources for depression recognition. Few of them need special tools like Electroencephalogram (EEG) [27] as well as those for speech identification [28] and face appearance [29] that may be regarded as interfering for patients. Contrary, the current suggested method examines user's posts, actions on social sites, and the characteristics of the surroundings taken out from publicly attainable information.

Tong et al. [30] proposed a new method known as Inverse Boosting Pruning Trees (IBPT) which shows a robust categorization capability over an openly attainable database having 7862 Twitter customers. For completely estimating the categorization ability of the IBPT, three actual databases were utilized from the UCI machine learning (ML) storehouse and the IBPT attained the greatest categorization outcomes as opposed to various modern methods. The outcomes proved that such a structure was good for recognizing social networks' customers having depression. Bilal et al. [31] reviewed modern classifiers utilized for recognizing depressed persons. The standard database consisted of messages and emoticons utilized in the social networking sites. The psychological procedure was merged with their corresponding emoticons for creating an automated network for the detection of depressed patients. The features from psychological procedure and emoticons were extracted and modern classifiers were instructed by utilizing various classifiers in which multiple associations of part-of-speech labels were utilized. Mustafa et al. [32] gathered instances of the latest Tweets of people ranging from (200 to 3200) Tweets for one user. Loads were allocated for every word from cheerful to sad after categorization by LIWC and instructed ML classifiers for categorizing the customers in three types of depression High, Medium, and Low. Choosing the best characteristics and their collaboration was useful for enhancing the achievement or precision of classifiers. A hybrid design by utilizing CNN (Convolutional Neural Network), as well as long short-term memory (LSTM), designs to discover depressed people by using general discussion-based messages information, recovered through Twitter was presented by Verma et al. [33]. The suggested technique was utilized on the Twitter database for contrasting their behavior for the discovery of depression. The suggested technique gave a precision of 92 percent as compared to other ML methods which provided the greatest precision of 83 percent.

Lei Tong et al. [34] implemented Natural Language Processing (NLP) methods as well as ML techniques for training the information as well as assessing the effectiveness of the suggested technique. A lexicon of words that were most frequently used was recognized in depressed accounts. The outcomes proved that the suggested technique notably enhanced achievement precision. The robustness, as well as the efficiency of the merged characteristics (LIWC + LDA + bigram), was successfully represented through Multilayer Perceptron (MLP) classifier giving having 91 percent correctness as well as 0.93 F1 scores. Best achievement can be attained by choosing correct characteristics as well as their association. Pampouchidou et al. [35] surveyed the techniques as well as designs for optical characteristics extraction, decreasing the dimensions, decision techniques for categorical as well as regression methods, and several fusion plans. A significant meta-estimation of provided outcomes, depending upon accomplishment measures was involved, recognizing common styles, as well as main unanswered problems, were taken into consideration for automated depression evaluation by using optical signals or infusion with vocal signals.

Islam et al. [37] suggested the depiction of a hierarchical designation, known as the multi-gated Liqarelu CNN (MGL-CNN). The design comprised of two segments: Firstly, a post-level task that was utilized for getting knowledge of the depiction of every post of the end-user. Secondly, a user-level task was utilized for attaining the complete description of the person’s psychological condition. Moreover, other depression recognition design by altering the count of gated units in the MGL-CNN was presented, known as Single-Gated LeakyReLU CNN (SGL-CNN). Test outcomes proved that the designs outperformed the earlier designs by using the Reddit Self-reported Depression Diagnosis database, as well as gave the best results on the ahead of time recognition of the Depression database. Depression estimation on Facebook information gathered was performed by Deshpande et al. [38] for inspecting the impact of depression. The outcomes proved that in various tests Decision Tree (DT) provided the greatest correctness than other ML methods for detecting depression. Trotzek et al. [39] implemented NLP on Twitter feeds for carrying out psychological estimation. User's Tweets were categorized as neutral or negative, based on an administered list of characters for recognizing depression proneness using SVM and Naive-Bayes. The outcomes were demonstrated by utilizing the main classification measures consisting of F1-score, precision as well as uncertainty grid. Chen et al. [40] proposed ML designs based on texts on a social network for the premature recognition of depression. In particular, CNN based on various character insertions was calculated as opposed to classification based on user-level linguistic metadata. The presently used common Early Risk Detection Error (ERDE) score as a measure for recognition structures was inspected at a detailed level as well as its shortcomings were demonstrated. Extraction as well categorization of a person's psychological characteristics based upon the LSTM system was presented by Stephen et al. [41]. Emojis were utilized as characteristics extraction as well as designing for document-level thought estimation in certain areas as well as attained better outcomes. The outcomes were primarily compatible with the discoveries of the Edinburgh Postnatal Depression

Table 2. *Related work.*

Author Name	Year	Proposed Method	Dataset Used	Performance Metrics	Improvements	Compared with
Uffaq Bilal et al., [31]	2020	POS Classifiers (10-fold cross-validation)	Tweets and Emojis	Accuracy rate (%)	It will utilize a novel approach to dig-out more type of characteristics	SVM NB KNN DT
Mustafa, R et al., [32]	2020`	TF-IDF LIWC	Twitter Social Media	Recall Precision F-score AUC	Extracting further more detailed data from stressed Twitter user Tweets.	SVM RF DCNN NN
Verma, B et al., [33]	2020	CNN LSTM	Twitter	Accuracy F1-score Recall Precision	In further work, will take into consideration the Facebook and Twitter information due to the threat of growing stress problems.	LR NB SVM KNN DT
Lei Tong et al., [30]	2019	New classifier using CBPT	Three UCI repository Datasets Twitter	Mean accuracy Standard deviation (SD) F1-score	This research work will search the SI (semantic information) of consumer's posts by utilizing the suggested model and other methods.	Discrete Ababoost Real Ababoost XGboost LogitBoost LightGBM KiGB Ababoost+PT
Tadesse, M. et al., [34]	2019	TFIDF LIWC MLP	Reddit	Accuracy Precision Recall F1-score	Will examine the relation between the consumer's personality and their stress regarding nature in SM (social media).	LDA SVM LR Ada boost
Pampouchidou, A et al., [35]	2017	PCA Regression GMM DF	Depression Dataset	Accuracy Precision Recall F-Score TP TN FP FN	Will make apparent that VC (visual cues) required to be supplemented by data from other models.	SVM NN RF
Roa G, et al., [36]	2020	MGLCNN	RSDD	F1 Precision Recall	Future work: will work on the application of MGLCNN and SGL-CNN to normal document level SA.	MNB BoW-SVM CNN
Islam, M. R et al., [37]	2018	LIWC	Facebook Depression Building Ground Truth	Recall F-measure	It will plan to utilize another method to extract the paragraph from more categories of characteristics.	SVM DT KNN Ensemble
Trotzek, M, et al., [39]	2018	CNN	Reddit	FP FN TP TN	-	FastText Wiki Glove W+N Glove Crawl FastText

						W+N
Chen Y et al., [40]	2018	LSTM	WeChat user	Edinburgh Postnatal Depression Scale WeChat Circle	-	-
Stephen, J. J t al., [41]	2019	AFINN	Twitter AADowd	WAS	The recent system may be updated to check all SM event for the users	-
Almouzini, S et al., [42]	2019	Supervised Learning Method	Twitter	F1-score Recall Accuracy Precision	The performance will improve by additional features of online Arabic users	RF NB Adaboost Liblinear
Kumar, A, et al., [43]	2019	Ensemble Vote Classification	Twitter	Accuracy F-score	The further model may analyze d on different users.	MNB GB RF
Shrestha, K et al., [44]	2018	ML AI LIWC	Twitter Data	-	Will develop novel NLP methods	MSR MR NB SVM LR DT RF HMM
Bhargava, S, et al., [45]	2018	Supervised ML	Social Network Sites Twitter	Classifier accuracy	It will develop a web-application. It will detect the multiple senses of the sentences.	NB MNB LR Linear SVM
Orabi, A. H, et al., [46]	2018	DL Word embedding optimization CNN	CLPsych2015 Bell let's Talk dataset	Accuracy F1 AUC Precision Recall	It will calculate against more DL models.	RNN
Zogan, H., et al., [47]	2022	Hybrid-deep learning based methodology for depression recognition	-	F1-Score Precision Accuracy Recall	In future, mixture of long and short content, URLs, web pages, and images will be used to enhance the proposed model	SVM NB (Naïve BAyes) MDL (Multi-modal dictionary learning) CNN Hierarchical Attention Neural Network
Tirtopangarsa, et al., [48]	2021	KNN (K-nearest neighbor) technique for depression identification	Twitter Data	Accuracy	Hybrid optimization technique will be implemented to improve the accuracy	KNN
Loh, H. W., et al., [49]	2021	CNN (Convolutional neural network) based methodology for depression recognition	MDD (Major Disorder Dataset)	Sensitivity F1-score Precision Specificity Accuracy	For more reliability, proposed model will be trained with more number of samples	CNN LSTM

Akbari, H., et al., [50]	2021	Empirical Wavelet Transform based technique	EEG signals based data	Sensitivity Accuracy Specificity	Pre-trained feature selection technique will be implemented for more efficient results	ANN SVM LR CNN KNN
Ferraro, et al., [51]	2020	Machine learning based methodology	Reachout Mental Health Dataset	F1-score	More data will be collected in future	KNN Naive Bayes MLP RNN LSTM
Amanat et al.	2022	LSTM with RNN	Tweets from Kaggle	Accuracy, Pre, Rec, F1-Score	Implementing hybrid recurrent neural network to observe behaviour of mentally disturbed people.	SVM,NB
Mostafa et al.	2023	FFF-SA	Arabic Tweets	Accuracy	Applying proposed and other deep learning models on additional Arabic datasets	Lexicon based, Machine
Obagbuwa et al.	2023	SVM, LR,RF,XGB	Twitter Posts	Accuracy, Computation Time	To reduce computational time, while also improving model accuracy.	SVM, XGB, LR, RF

Scale. Such a technique considerably reduced the screening time as well as decreased the doctor-patient interaction expenses. It showed productive importance for certain fields of thought categorization jobs as well as gave recommendations for document-level emotional estimation. Almouzini et al. [42] presented an effective technique for recognizing the extent of depression in Twitter users. Emotional scores estimated were merged with various sentiments for giving a good technique for computing depression scores. Such a procedure helped underscore different features of depression that were not acknowledged earlier. The key purpose was to give good knowledge regarding depression extents in several users. A new survey that uses Arabic information to observe depressive feelings in the web public was proposed in Kumar et al. [43]. The tests were conducted based on information gathered from Twitter in the Bay Area, which recognized those who admitted in their tweets that they had been diagnosed with depression. Another set of tweets from non-depressed people was used as a common set to create a collection with honesty tags (depressed and non-depressed). After that, a predictive design was created based on supervised learning techniques (Random Forest, Naïve Bayes, AdaBoostM1, and Liblinear) to estimate whether a person's tweet was sad or not and they were able to achieve an accuracy of 87%. Shrestha et al. [44] proposed AD estimation design, for depression estimation in real-world Tweets. A worry-related lexicon was created for recognizing the existence of uneasiness signs. Time, as well as the frequency of Tweets, was measured for instability as well as judgment polarity investigations were carried out for locating irregularities in posting actions. The design was instructed by utilizing 3 classifiers (multinomial naïve Bayes, gradient boosting, and random forest) as well as maximum polling was done by utilizing group polling classifiers. Outcomes were calculated for Tweets of sampled 100 people and the suggested design attained a precision of 85 percent. Bhargava et al. [45] worked on creating ML designs for recognizing the phases of depression of Twitter users through the person's public Tweets as well as various other tasks on Twitter. It gave background on depression, usage of Twitter for estimations as well as machine learning techniques. Earlier researches were surveyed in which ML techniques were used for recognizing depression.

Orabi et al. [46] utilized deep learning techniques for depression recognition from Tweets on the end-user level. Tests were carried out on two openly available databases, CLPsych2015, and Bell Let's Talk. The tests proved that CNN-based designs outperformed RNN based designs. Zogan et al. [47] presented a multiple aspect-based depression identification utilizing a hierarchical attention network for detecting and recognizing depressive people on the internet and reported that using the power of integrating deep convolutional neural network and multi-aspect parameters, it outperformed other approaches. The author combined person comments using Twitter's additional features and encapsulated person comments and estimated the significance for every Twitter post and extracted patterns semantically from user tweets. They reported that the algorithm forecast results when identifying depression in Facebook users who publish comments openly.

Tirtopangarsa et al. [48] designed a supervised learning-based approach for identifying depression utilizing social media posts and extracted 90 distinct features. The attributes generated after feature extraction techniques effectively identify depression with GB (Gradient Boosting), an ensemble predictor, having an accuracy of 98 percent. Loh et al. [49] presented a new deep convolutional neural network and spectrogram visuals. To create spectral visualizations of MDD/ healthy patients participants, the STFT (Short-Time Fourier Transform) was initially applied on the EEG data. The CNN model was then given such spectrogram visuals to recognize MDD/ healthy patient-participants automatically. EEG signals from 34 Patients with mdd and 30 healthy individuals were acquired from a public dataset for this investigation. Hold-out verification yielded the most outstanding classification, precision, F1-score, sensitivity, specificity, and accuracy of 99.40 percent, 99.55 percent, 99.70 percent, 99.48 percent, and 99.58 percent, correspondingly. For the categorization of depressed and non-depressed EEG recordings, Akbari et al. [50] suggested a new approach based on centring correntropy as well as EWT (Empirical wavelet transform). EWT decomposes EEG data into cycles, and the distinguishing characteristic of routines was generated and input to K-nearest neighbours and support vector machine models. EEG readings from 22 depressed and 22 healthy patients were used to test the suggested approach. Using the SVM classification method, authors were able to accomplish 98.76 percent, 98.47 percent, and 99.05 percent categorization accuracy, specificity, and sensitivity in a 10-fold cross-validation procedure. A database from the Reachout psychological health community for youngsters was employed by Ferraro et al. [51] to improve a crisis comment classification utilizing ML (Machine learning) and NLP (Natural language processing) technology. Amanat et al. [52] developed a LSTM neural network (NN) model to predict depression from writing. The model had two hidden layers and was trained on textual data to detect signals of depression based on semantics and content. It achieved 98.8% accuracy, demonstrating the potential of deep learning methods like LSTM combined with recurrent neural networks to accurately identify depression from written text. A 2023 analysis by Mostafa et al.[53] proposed a sentiment analysis method for Arabic data using k-fold cross-validation. They developed a forward fusion feature selection technique for sentiment analysis (FFF-SA) that applies different ML classifiers on incremental feature subsets of the Arabic dataset. The proposed FFF-SA approach highlights the potential of customized feature engineering and ensembling methods for multilingual sentiment analysis applications. Obagbuwa et al. [54] developed a machine learning sentiment analysis method to predict depression levels from online posts. Using a Twitter dataset, they tested different ML models including logistic regression (LR) and SVM for the prediction task. Their proposed approach performed better with LR compared to SVM. Table 2 presents the different articles reviewed with emphasis on research methods, datasets, performance metrics, and future suggestions. There also are a number of works done in this topics and reported [55-58].

3. Comparative Analysis

For analyzing the performance of existing methods, a comparison in their performance is depicted in Table 3. The comparison depends on performance metrics like accuracy, precision, recall, f-score. Figure 1 shows the comparison based on accuracy of existing methods for depression analysis. Different existing methods such as Ada-Boost, random forest, MLP, LSTM, decision tree, CNN, etc., are compared. It can be seen that Multi-layer perceptron has attained maximum accuracy. Figure 2 depicts the precision values of existing methods for the comparative analysis. The comparison shows that DCNN and SVM have achieved the maximum value of the precision followed by MLP Figure 3, F1-score values of depression detection existing methods are presented graphically. The comparison shows that MLP has achieved maximum value of F1-score. Also, SVM and DCNN have attained the similar values of F1-score.Figure 4, recall values of depression detection existing methods are presented graphically. The comparison shows that Ensemble boosted tree has achieved maximum value of recall followed by MLP.

4. Conclusion and Discussion

Various methods used for depression sentiment analysis are reviewed in this paper. Various existing machine learning based techniques were studied such as Support Vector Machine, Decision Tree, Naïve Bayes, Logistic Regression, Maximum Entropy etc. Also deep learning based methods were reviewed such as Deep Neural Network (DNN), Convolutional Neural Network (CNN), Logistic Regression (LR), Recurrent Neural Network (RNN) etc. The various datasets such as HASH, EMOT, and ISIEVE, etc. were used for experimental purpose that provided effective results. In this survey we have included all standard datasets and presented comparison table based on precision rate. Different applications and datasets are also presented for sentiment analysis in depression. The problems which occur in sentiment analysis of depression are also discussed. Several feature extraction and classification techniques are even studied for improving the performance of the system. The findings of results, based on precision rate showed that all of the classifiers got results between 60 to 95%.The studies of various techniques conclude that deep learning based techniques are provided effective results but training of models is little bit challenging. At the time of surveying, it was discovered that a single technique is not capable of accurate sentiment analysis in depression. In future, we can also

Table 3. *Comparative analysis of existing methods.*

Methods	Accuracy	Precision	Recall	F1-score
DCNN [32]	-	0.93	0.78	0.85
SVM [32]	-	0.93	0.78	0.85
RF [32]	-	0.84	0.84	0.84
AdaBoost [34]	79	0.84	0.79	0.81
MLP [34]	91	0.90	0.92	0.93
LSTM [36]	-	0.44	0.33	0.44
Bi-LSTM-attention [36]	-	0.62	0.39	0.48
LSTM attention [36]	-	0.54	0.35	0.42
Decision tree [37]	-	0.59	0.84	0.69
KNN [37]	-	0.59	0.53	0.56
Ensemble boosted tree [37]	-	0.58	0.96	0.72
Multi-nomial naïve bayes [38]	83	0.836	0.83	0.832
SVM [38]	79	0.80	0.79	0.79
AdaBoostM1 [42]	55.2	56.4	55.3	53.2
RF (Random forest) [42]	83	85.7	83.1	82.8
Naïve Bayes [42]	75.6	75.8	75.6	75.6
Lib-Linear [42]	87.5	87.6	87.5	87.5
Multi-channel CNN [46]	83.11	81.62	84.43	82.25
Bi-LSTM [46]	80.51	80.51	83.803	80.035
Multi-channel pooling CNN [46]	82.46	80.87	83.49	81.51
Multiple aspect Features with MLP [47]	0.82	0.84	0.82	0.80

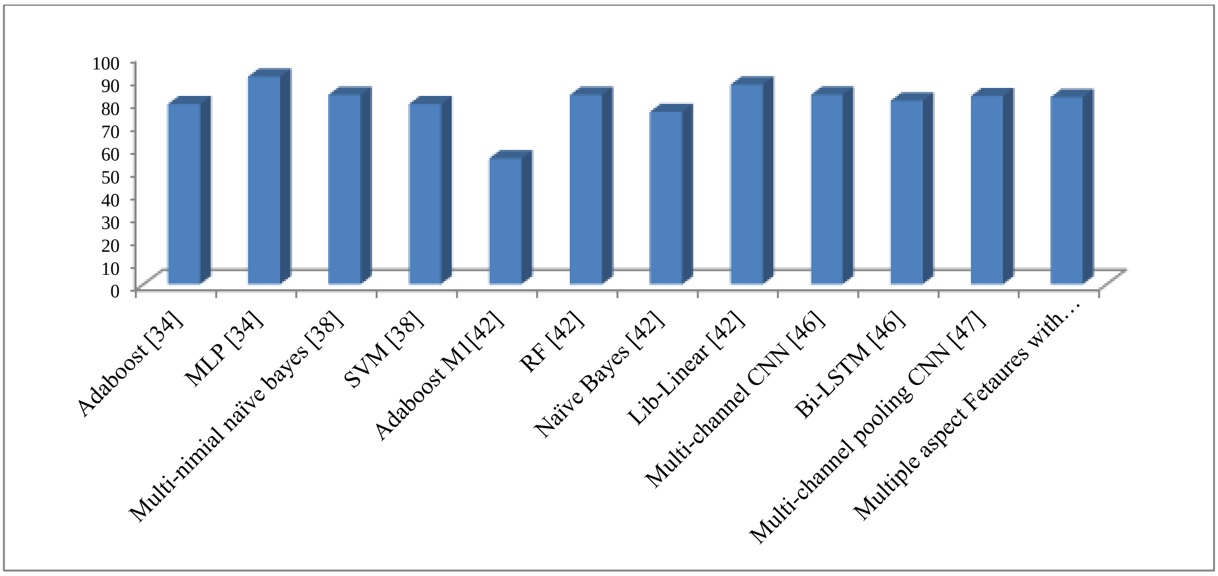

Figure 1. *Comparative analysis based on accuracy.*

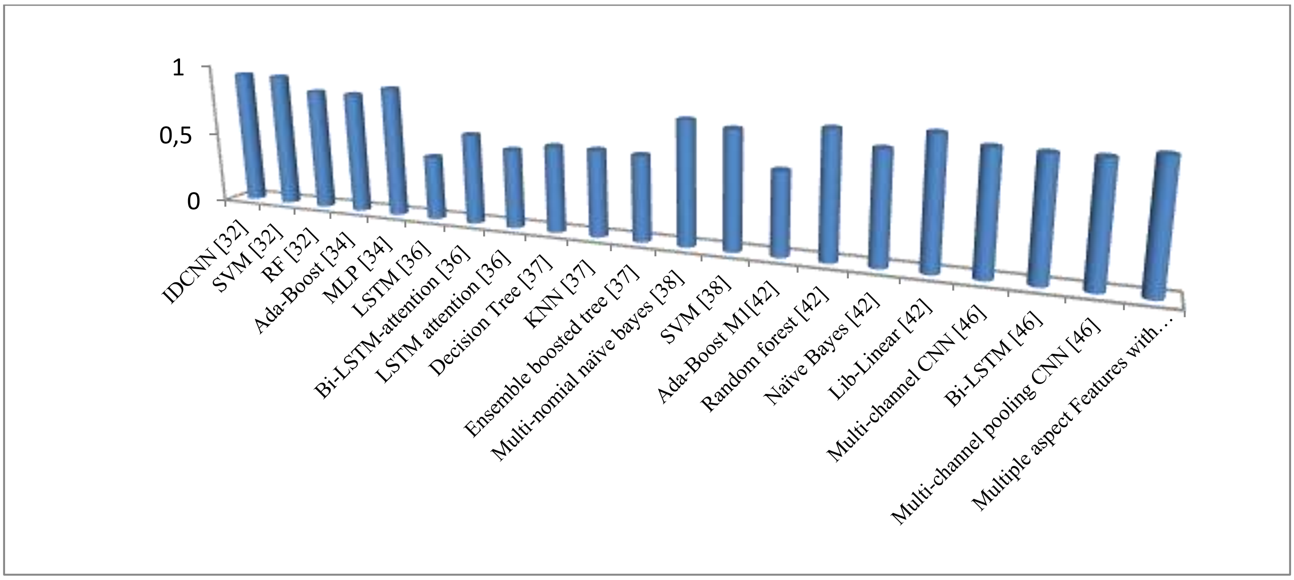

Figure 2. *Comparative analysis based on precision.*

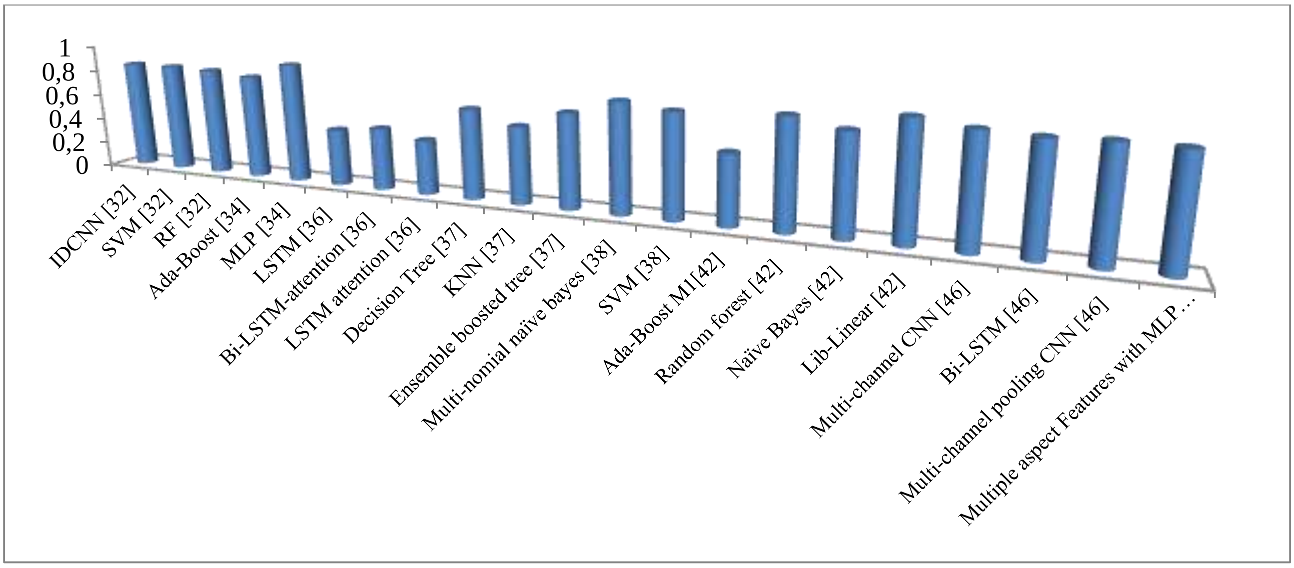

Figure 3. *Comparative analysis based on F1-score.*

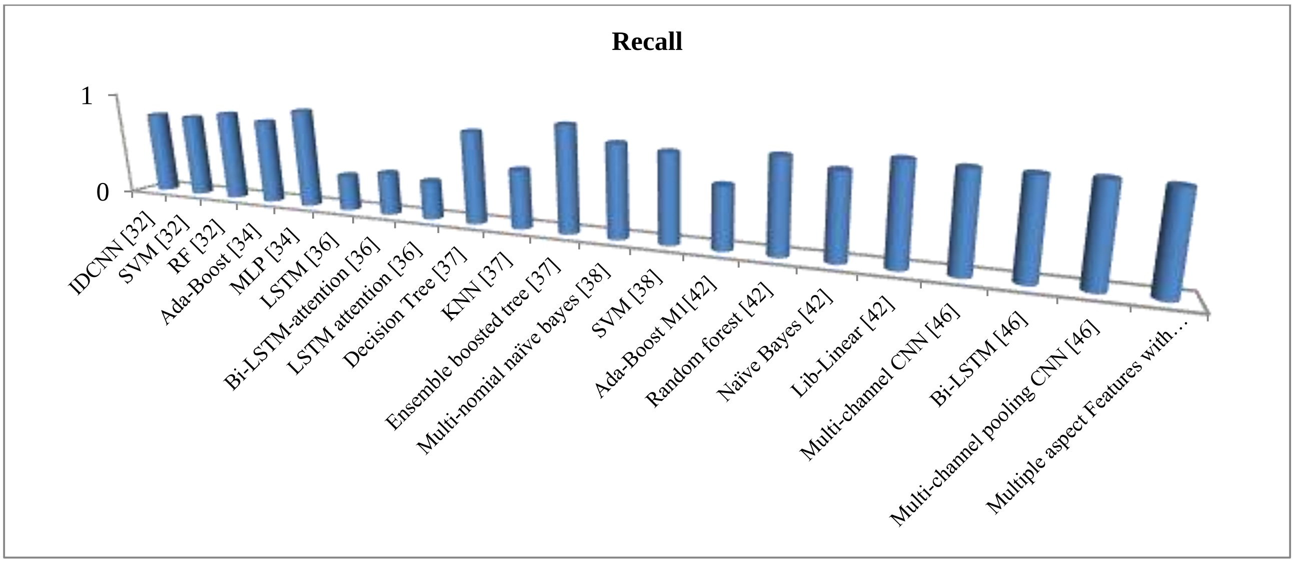

Figure 4. *Comparative analysis based on recall.*

analysis the various techniques such as techniques can be implemented which can be used for checking the online activity of an individual in closed surroundings like a rehab clinic and where the behaviour of a person can be monitored full time.

- A combination of classification and feature extraction methods may be proposed and larger datasets information as well as statistical data could be used for evaluation and new issues such as Post-Traumatic Stress Disorder (PTSD) from the perspective of a social network service provider could be explored without compromising the user engagement.
- A web-based application to check the mental disorder or mental condition of the person can be created for use in future.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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