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Feature Based Depression Detection from Twitter Data Using Machine Learning Techniques

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Abstract. The statistics presented by the World Health Organization attribute depression to be a primary cause of concern globally, leading to suicide in the majority of the cases if left undetected. Studies show that depression generally has an impact on the writing style and corresponding language use. The primary aim of the proposed research is to study users' posts on Twitter and identify the attributes that may indicate depressive symptoms of online users. The paper employed machine learning approaches and natural language processing techniques for training our data and evaluating the efficiency of our proposed method. The work proposed a numerical score for each user based on the sentiment value of their tweets and demonstrated that this feature can detect depression with an accuracy of 78% with the XGBoost classifier. This attribute is combined with other Linguistic features (N-Gram+TF-IDF) and LDA to achieve an accuracy of 89% using the Support Vector Machine classifier. According to the proposed research, proper feature selection and their combinations help in achieving better improvement in performance.

Keywords: Depression, Natural Language Processing, Machine Learning, Twitter, Social Networks

1 Introduction

Mental Illness is a serious public health issue worldwide because of its prevalence as well as the pain, morbidity, dysfunction, and economic burden that it causes. According to World Health Organization (WHO), the National Mental Health Survey 2015-16 reported that roughly 15% of adults in India require active care for more than one mental health issue [1]. Among all classes of mental disorders in India, Idiopathic Development intellectual disability (4.5%) is the most common, followed by Depressive disorders (3.3%) and Anxiety disorders (3.3%) [2]. According to Lancet studies, there is a significant correlation between the incidence of depressive illnesses and the suicide death rate at the state level in India [3]. Depression is mostly characterized by persistent sadness and lack of interest in previously enjoyed activities as well as an inability to carry out daily activities for at least two weeks [4]. Therefore, an early diagnosis of depression is crucial for effective treatment [5]. However, a concern remains that a wide range of people suffering from depressive symptoms does not seek professional help or clinical advice due to the social stigma associated with it [6]. As a result, people are resorting to informal resources such as social media to solve their problems.

With the introduction of social media, people suffering from mental health issues implicitly or explicitly share their feelings and experiences through online forums, tweets and blogs as a way of relief [7][8]. Research in psychology states that there is a strong connection between the mental wellbeing of an individual and its corresponding language use. Twitter nowadays has become the most popular social media for research on Sentiment Analysis. Researchers believe that the identification of depression and other mental health problems is possible through the analysis of Twitter posts. They are inspired by these online activities to develop new forms of prospective health care solutions and early depression detection systems. This is achieved by utilizing Machine learning algorithms along with Natural Language Processing (NLP) techniques for identifying depression in user posts. Several researchers extracted several single set features groups like N-grams [9], Bag-of-Words [10][11], LIWC [12], or LDA [13] [14] for identifying depression in user's posts. Some other works used various machine learning algorithms for comparing the performance of these individual features [15][16][17][18][19]. Some current research works had

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focused on improving the detection accuracy by combining some of the features. The authors in [20] combined N-Gram+LIWC to improve the detection accuracy over single set features. Similarly, in [21] the authors used advanced text pre-processing and used a combination of Bag of Words, LDA, and TF-IDF and used Convolutional Neural Networks (CNN) to improve the performance. According to a study by Tadese et al. [22], the use of combined features can result in higher performance. They compared the performance of a single feature such as bigram with Support Vector Machine (SVM) classifier to reach 80 percent accuracy. They demonstrated the effectiveness of combined feature (LIWC+ LDA+ bigram) with Multilayer Perceptron (MLP) to attain an accuracy of 91%. Over the last few years, there is a growing body of literature that deals with the early detection of mental illness by utilizing social media information [23][24][25].

Although a substantial amount of progress is already being made in this field, there are still some challenges to overcome. In this paper, we aim to achieve high performance in early depression detection by considering a proper feature selection by analyzing users' posts from Twitter. The proposed work extracted various features from the dataset and experimented with different machine learning techniques for improving the performance of depression detection. N-Gram modeling was used for calculating the co-occurrence probability of each text as anagram or bigram by using the TF-IDF method. Latent Dirichlet Allocation (LDA) was selected as one of the successful aspects of the topic modeling. We assessed emoticons used by a user and assigned a score to them. Furthermore, we established a metric for Sentiment Analysis of user posts. Finally, these sets of features are used with classification techniques for detecting depression in users' posts. The performance of each feature individually and their multiple combinations are studied.

Our main contribution is as follows:
i) We reviewed the literature on different emotion detection methods for detecting depression.
ii) We selected Linguistic, Topic, Emoticon, and Sentiment features for our research problem and demonstrated the predictive power of each type of feature as well as their multiple combinations.
iii) We defined a metric to assign each user a polarity preserving numerical score based on the sentiment value of their tweets.
iv) We employed machine learning techniques for demonstrating the advantages of combining different features for achieving high performance in depression detection.

The remainder of the paper is organized as follows. In Section 2, we discuss the literature on depression detection. The problem statement for this specific research problem is given in Section 3. The dataset is described in Section 4 and the methodology of our research is described in Section 5. Section 6 describes our experimental results. Finally, the conclusion is provided in the last section.

2 Literature review

In this section, we aim to provide a broad overview of the different research relating to the detection of mental illness on social networks.

Choudhury et al. [26] considered an important but under-reported mental health concern among a large number of the female population. They concentrated on utilizing Twitter posts for building a predictive model about the imminent influence of childbirth on the disposition and behavior of new mothers. Twitter posts of 376 mothers were measured along dimensions such as emotions, social networking engagements, linguistic style, and social network usage for detecting postpartum changes. [27] aimed to examine if the level of apprehension for a suicide-related tweet could be solely determined based on the content of the tweet utilizing both human coders and machine learning classifiers.

In [28], the authors suggested that social media is increasingly being used by people to share their emotions and daily lives. They leveraged Twitter posts to construct a well-labeled data set on depression and mined six feature groups consisting of depression-related criteria from both clinical and online social behaviors. The feature groups were used to develop a multimodal depressive dictionary learning model for detecting depressed users on Twitter. In [29] the authors closely studied the relationship between mental wellness and social media. They associated anxiety-depression with irregular thinking processes, agitation, and insomnia. Using posting patterns and linguistic cues, they proposed a prediction model using real-time tweets for anxious depression prediction. The feature vector consists of the sentiment, timing, frequency, contrast, and the word and majority voting using an ensemble voting classifier are done. In [30], the authors used a collection of machine learning algorithms to classify the positive and the negative emotions of users using Twitter tweets and compare the performance with deep learning approaches. The authors concluded that among all the models, CNN-based deep learning performs much better than the machine learning models. Twitter posts are also used in [31] to create training and test datasets on depression and classification are done using Naive Bayes' classifier.

An observation by the authors [32] states that with the increasing use of social media people talk about their depression specifically suicidal thoughts on social media. They analyzed various profiles from Twitter and used several accounts and tweet-related features for detecting suicidal profiles. A dataset of people who have already committed suicide was used to find the effectiveness of the approach. In the same context, recent work in [33] draws our attention where the authors considered classification tasks to detect depression by processing text messages of Reddit users. Various baseline features were considered, including the TF - IDF, bigrams, and embedding as well as more complex features like stylometric and morphology.

Authors in [34] use the user's previous writings on Reddit to detect early signs of depression using a standard bag of words, surface features, and more linguistic-related features to build a supervised prediction model for automatically detecting early signs of depression. In [35] authors proposed a Feature Attention network consisting of a set of feature networks ranging from depressive symptoms, sentiments, ruminative thinking, and writing style and used deep learning for detecting depressed users. In [36], the authors explored various methods for early detection of depression using singleton and dual approaches of machine learning. The singleton uses a random forest classifier with 2 threshold functions while the dual approach uses 2 RF classifiers that are independent of each other, one to detect depressed users and others to identify non-depression. In [37] the authors use two different methods for early detection of symptoms-the first one uses time and writing patterns of the user and the second one includes clues from the shared text and tweets. In [38], the authors addressed the early detection of suicide through deep learning LSTM-CNN and machine learning based classification approach on Reddit social media posts. They analyzed user posts online consecutively over a time period and provides an early detection using a combination of learning algorithms.

There are several shortcomings in the existing literature, even though some of the above-mentioned work has considered sentiment, linguistic and topic analysis for depression detection. Only a limited number of research works have focused on using Sentiment [39], Emotional, Linguistic and topic features separately, but no well-known studies have merged all these features and applied them to the same dataset to observe the deviation in the results. We address these shortcomings in our present work by attempting to detect depression from Twitter comments. We applied various machine learning approaches and used various feature combinations for detecting individuals who are suffering from depression.

3 Datasets

The proposed work uses Twitter data to train our algorithm for depression detection. Using Twitter APIs, we created two datasets, one for depression and one for non-depression users. For every Twitter user, we collected a simple set of statistics about their profile as well as their tweets for a period of one month starting from an anchor tweet. For the hashtags, links, replies, and @mentions we used the numbers and took the average per tweet. A social media session consists of a tweet and the replies and comments associated with it. In our work, we are considering each tweet as a post for a session instead of merging all the tweets for a particular user. The proposed work aims to work on each tweet individually and determine whether a user is depressed or not by processing as few tweets as possible. In addition, working with individual tweets allow us to merge tweets easily up to a fixed point, i.e., k. The statistics for the dataset are given in Table 1.

Table 1. Dataset Statistics

Description	Depressed dataset	Non-Depressed dataset
Number of Twitter users	256	218
Number of tweets	3082	4687
Mean number of tweets per user	12.039	21.5
Mean tweet length (in words)	13.951	12.374
Mean number of emoticons per user	24.144	30.45

4 Methodology

Due to the diversity of user behavior on social media and the intricacy of their posts, we propose using four machine learning models on a specified feature set to identify depressive individuals. The model requires two inputs for each user, one for each attribute. The first input represents the tweets of each user using a set of linguistic features. We performed a word-by-word sentiment and emotional analysis of the tweets to determine the personality of each user and this feature acts as a second input to our model. The output from both the attributes is fused and this is fed to our model for prediction. Fig. 1 depicts the framework of our methodology which consists of data preprocessing, feature extraction, analysis followed by classification and output. The following sections describe our approach.

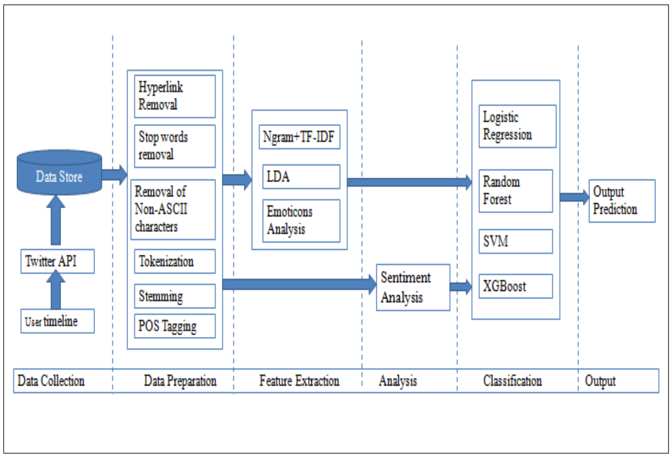

Fig. 1. The methodological framework of Twitter data analysis for analysis of depression

4.1 Data Preprocessing

Data collected from online social media cannot be directly used for feature extraction due to the presence of various noises that are prevalent in the raw data. This causes problems in word matching and semantic analysis. The problem is more exaggerated as data from online social media may contain grammar and spelling mistakes, emojis, and other unwanted characters. Therefore, we need to preprocess the data to ensure that our computational model accomplishes reliable predictive analysis. We carried out the following data preprocessing procedures depicted in Fig 1.

4.2 Feature Extraction

These consist of the features that represent the user's behavior on social media in writing a post/comment and are therefore indicative of the user's personality. Each of these features is described in the next subsections.

Emojis/Emoticons Sentiment – Users use emojis to express their emotions using non-verbal elements and simple icons. Emojis are useful for drawing the interest of the reader. Emojis could provide us an idea behind the sentiment of any texts or tweets and it is vital to distinguish between positive and negative sentiment text. Tweets posted by users usually contain a lot of emoticons which can be categorized into positive, negative, and neutral.

1. Count the frequency of positive, negative, and neutral emoticons in each tweet.

2. Sum up the frequencies of each type for an individual user's tweets to get the sum for each user.

The final output is three values corresponding to positive, negative, and neutral emoticons by the user.

Sentiment Analysis- For performing sentiment analysis, initially we employed the SentiWordNet library in Python for assigning positivity negativity and objectivity scores to each word in a tweet. The score of each tweet is assigned using equation (1).

$$\text{Tweet\_Score}_k = \frac{\prod_{i=1}^{n} Score(i)}{w} \quad (1)$$

Where Score(i) is the positive or negative scores of each word in the tweet and w is the number of words in the tweet. Taking the product of the score of each word helps us to maintain the positivity or negativity sign. Since multiplying the scores may result in large values, we normalize the scores by using equation (2).

$$\forall_k \text{ Norm }(\text{Tweet\_Score}_k) = \frac{Tweet\_Score_k - Min(Tweet_{Score_k})}{Max(Tweet_{Score_k}) - Min(Tweet_{Score_k})} \quad (2)$$

We obtain the score for each user by taking the mean of all the normalized scores of overall tweets. The equation for calculating the scores for each user is given in equation (3). Here n is the number of tweets for each user.

$$\forall_j \text{User\_score}_j = \frac{\sum_{k=1}^{n} Norm(Tweet\_Score_k)}{n}$$
(3)

LDA features: Topic distribution or topic modeling is a class of statistical modeling techniques that are used to identify abstract topics in a group of text documents. This technique can be used for understanding, organizing, and summarizing textual information from a corpus. It also helps for identifying the hidden patterns within a text based on the number of topics provided by the user in advance. The latent topical information in any collection of documents represented by a group of words (topics) can be found using this method. In our work, we aim to apply the unsupervised LDA (Latent Dirichlet Allocation) for extracting the hidden distribution of various topics from user tweets.

For our study, we experimented with different values for the number of topics and found 10 to be a suitable value. By selecting 10 topics, we are achieving an accuracy score of 86% using LR. Table 2 shows the keywords that are associated with 5 topics.

Table 2. Generated text using the LDA feature on the depression dataset.

Topic 1	like, love, know, one, want, sorry, sad, cry, sick, hate, die, friend, know, cut
Topic 2	Think, want, Feel, ignore, understand, listen, notice, need, nothing, understand
Topic 3	fat, people, someone, something, never, pain, break, away, smile, sorry, alone
Topic 4	hurt,annoy,one, life, always, care, mean, lose,back,stay,leave, tire,try
Topic 5	Day, really, night, anyone, shit, really, break, better, sleep, bed

Linguistic features: N-gram modeling and TF-IDF - N-gram modeling is used for examining the features that are present in posts. It is commonly used in NLP as a feature to calculate the co-occurrence probability of each text as a unigram or bigram. For n-gram modeling, TF-IDF is used as a statistical measure for highlighting the importance of a word concerning user posts. The idea behind this approach is to reduce the impact of frequently occurring less informative tokens and consider more informative tokens that occur less frequently. The tokens having a higher TF–IDF value are present in a particular post and are not present in other posts. We removed the stop words from the dataset and restricted the term –document matrix to most frequent unigrams and bigrams. We choose the top 100 unigrams and bigrams for each type of post. This is shown in Fig 2 and Fig 3. The words that appeared with a high frequency are depicted in both figures.

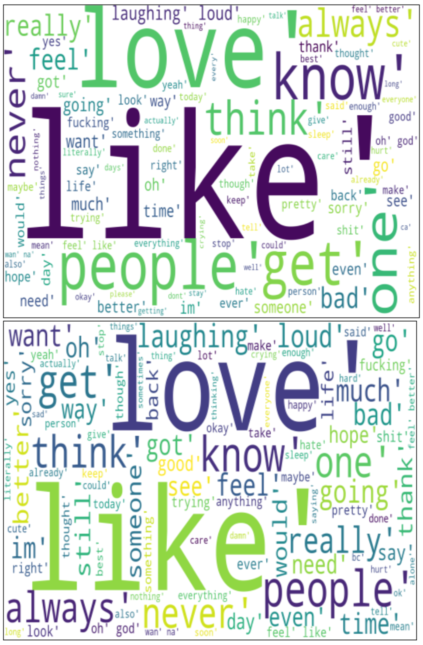

Fig. 2. Depressed posts (a) Unigrams b) Bigrams

Fig. 3. Nondepressed posts(a) Unigrams b) Bigrams

Analysis of our results indicates that the lexicon that is predictive of depression includes words that contain negative emotions, feelings, self-obsession, suicidal thoughts, hostility, anger, negative words, hopelessness, meaninglessness, and present tense. Depressive posts also contain lexicons related to bodily symptoms of fatigue, insomnia, low energy, or hyperactivity. In contrast, the lexicons of standard posts contain words that describe past events, social relations, and family-oriented words.

5 Experimental Evaluation

5.1 Classification Models

In this step, we consider several classifications approach for constructing the prediction model and estimating the likelihood of depression among the users. For training purposes, we used 80% of the dataset and the remaining dataset is used for testing. The dataset is partitioned concerning social media sessions and each session consists of all its tweets. Each tweet is labeled with a class-either depressive or not depressive. The classifiers used in developing the model consist of Logistic Regression, Random Forest, Support Vector Machine, and XGBoost. For evaluating the performance of the above-mentioned approaches, we used the following evaluation metrics: i) Accuracy ii) Precision iii) Recall iv) F-measure.

5.2 Classification Results

The focus of this research is to detect depression by analyzing the selected user comments. We begin by running the text classification techniques on the whole dimension feature space collected from the dataset. For comprehending the importance of the different features that are extracted from the dataset, we applied four major classifiers specified in Section 5.1, each classifier using all the feature types.

The experiments are evaluated by using 10-fold cross-validation on all levels of testing data. We evaluated the performance of the linguistic features with the classifiers and observed an improvement in prediction. An accuracy of 87% and F1-Score of 0.86 is observed with bigram+TF-IDF with SVM classifier. This is followed by LDA with the LR classification model (86%,0.85). The combination of Linguistic features (Trigram+TF-IDF+LDA) performs better (87%,.87) than when the features are combined with bigrams. Among the classifiers, XGBoost outperforms the others in terms of unigram features and combination with LDA. SVM performs better for bigram and trigram features in combination with LDA.

Table 3. Performance metrics of machine learning classifiers based on linguistic features

	LR	RF	SVM	XGBoost
Unigram+TF-IDF				
Accuracy	0.70	0.65	0.70	**0.71**
Precision	0.69	0.65	0.69	**0.69**
Recall	0.70	0.57	0.67	**0.69**
F1-Score	0.69	0.54	0.68	**0.69**
Bigram+TF-IDF				
Accuracy	0.82	0.65	**0.87**	0.80
Precision	0.81	0.72	**0.86**	0.79
Recall	0.82	0.56	**0.86**	0.79
F1-Score	0.81	0.52	**0.86**	0.79
Trigram+TF-IDF				
Accuracy	0.84	0.63	**0.84**	0.81
Precision	0.83	0.80	**0.83**	0.80
Recall	0.84	0.53	**0.83**	0.80
F1-Score	0.84	0.44	**0.83**	0.80
LDA				
Accuracy	**0.86**	0.61	0.70	0.71
Precision	**0.85**	0.30	0.70	0.69
Recall	**0.85**	0.50	0.70	0.69
F1-Score	**0.85**	0.38	0.70	0.71
LDA+Unigram+TF-IDF				
Accuracy	0.70	0.65	0.70	**0.71**
Precision	0.69	0.57	0.70	**0.71**
Recall	0.71	0.65	0.70	**0.71**
F1-Score	0.70	0.59	0.70	**0.71**
LDA+BiGram+TF-IDF				
Accuracy	0.82	0.66	**0.84**	0.81
Precision	0.81	0.80	**0.83**	0.80
Recall	0.82	0.56	**0.84**	0.81
F1-Score	0.82	0.51	**0.84**	0.81
LDA+Trigram+TF-IDF				
Accuracy	0.85	0.61	**0.87**	0.81
Precision	0.84	0.81	**0.86**	0.80
Recall	0.84	0.50	**0.87**	0.79
F1-Score	0.85	0.39	**0.87**	0.80

The sentiment Analysis score defined in this paper is functioning well as a single feature. It provides a 78 percent accuracy, using the XGBoost model (78,0.78). When used in conjunction with the Emoticon feature, it achieves an accuracy of 77 percent (77,0.77) using the LR model. A detailed analysis of the results is given in Tables 3 and 4. We combined the linguistic, topic, and emotional features and aimed to find out which combination performs best in terms of accuracy for depressed tweet classification.

Table 4. Performance metrics of machine learning classifiers based on Emotional Features

	LR	RF	SVM	XGBoost
Sentiment Analysis (SA)				
Accuracy	0.75	0.69	0.74	**0.78**
Precision	0.72	0.68	0.75	**0.77**
Recall	0.71	0.69	0.77	**0.72**
F1-Score	0.73	0.68	0.75	**0.78**

SA+Emoticons				
Accuracy	**0.77**	0.65	0.75	0.73
Precision	**0.75**	0.72	0.73	0.76
Recall	**076**	0.56	0.74	0.73
F1-Score	**0.77**	0.52	0.75	0.77

The Linguistic feature is used to complement the Sentiment Analysis feature. The best performance for depression detection in our research is achieved by Trigram+TF-IDF and SA+EA features. With an accuracy of 89% and 0.88 F1-score with SVM classifier, it has outperformed other feature combinations: LDA+Trigram+TFIDF+SA+EA (88%,0.87), LDA+Unigram+TF-IDF+SA+EA(86%,0.85), LDA+Bigram+TFIDF+SA+EA (85%,0.85), Bigram+TF–IDF+SA+EA (84%, 0.83) and Unigram+TF-IDF+SA+EA (77%,0.75).The classifier that performs best in most cases is the SVM followed by LR and XGBoost. The detailed analysis of the results for combined features is presented in Table 5. The comparison of the performance of various classifiers is shown in Fig 4.

Table 5. Performance metrics of machine learning classifiers based on Linguistics and Emotional Features

	LR	**RF**	**SVM**	**XGBoost**
Unigram+TF-IDF+SA+EA				
Accuracy	0.71	0.73	**0.77**	0.71
Precision	0.72	0.72	**0.75**	0.72
Recall	0.70	0.70	**0.73**	0.70
F1-Score	0.71	0.71	**0.75**	0.71
Bigram+TF-IDF+SA+EA				
Accuracy	0.82	0.65	**0.84**	0.80
Precision	0.81	0.72	**0.83**	0.79
Recall	0.82	0.56	**0.83**	0.79
F1-Score	0.81	0.52	**0.83**	0.79
Trigram+TF-IDF+SA+EA				
Accuracy	0.84	0.63	**0.89**	0.81
Precision	0.83	0.80	**0.88**	0.80
Recall	0.84	0.53	**0.87**	0.80
F1-Score	0.84	0.44	**0.88**	0.80
LDA+Unigram+TF-IDF+SA+EA				
Accuracy	**0.86**	0.61	0.70	0.71
Precision	**0.85**	0.30	0.70	0.69
Recall	**0.85**	0.50	0.70	0.69
F1-Score	**0.85**	0.38	0.70	0.71
LDA+Bigram+TF-IDF+SA+EA				
Accuracy	0.85	0.61	**0.87**	0.81
Precision	0.84	0.81	**0.86**	0.80
Recall	0.84	0.50	**0.87**	0.79
F1-Score	0.85	0.39	**0.87**	0.80
LDA+Trigram+TF-IDF+SA+EA				
Accuracy	0.83	0.63	**0.88**	0.80
Precision	0.84	0.81	**0.86**	0.80
Recall	0.84	0.50	**0.87**	0.79
F1-Score	0.84	0.69	**0.87**	0.81

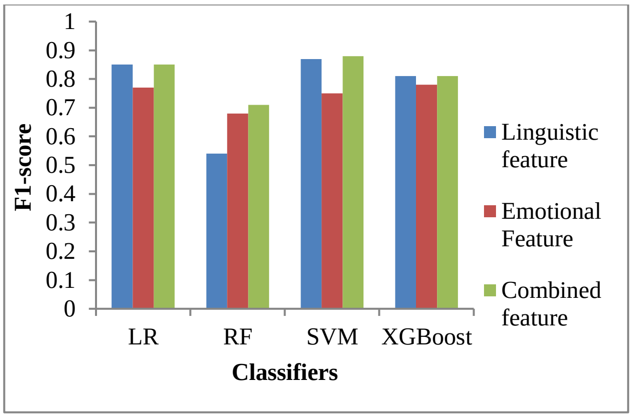

Fig. 4. F1-Measure on depression data set of different classifiers.

6 Conclusion and Future Work

In this research, we used Logistic Regression, SVM, Random Forest, and XGBoost classifier techniques for depression detection of emotional phrases in users' tweets for gaining a deeper understanding of the common perception behind depression. We demonstrated experimentally that all the features: Linguistic, Topic, Sentiment and Emotional features are successful in extracting features from the tweets that aid in depression detection. The SA measure defined in this paper performs well as a stand-alone feature using the XGBoost classifier. In combination with the linguistic feature, the SA measure gives good performance by using SVM and XGBoost classifiers. From our study, we can derive that the high performance in prediction can be achieved by the proper selection of features. The effectiveness of using combined features is shown with the SVM classifier achieving an accuracy of 89% in detection.

Despite our methodology's excellent success, there is still a lot of room for improvement and research, as seen by the value of the evaluation metrics. In future work, we intend to employ techniques for extracting more emotional features from the tweets. We also intend to employ new datasets for verifying the effectiveness and efficiency of our approaches. In addition, we believe that a detailed analysis of SA measures may aid in predicting the personalities of users based on their linguistic style. We hope this study will serve as a ground for future work in this direction.

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