

Identification of depressing tweets using natural language processing and machine learning: Application of grey relational grades

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ABSTRACT

Depression is a global public health concern that affects millions of people worldwide. Social media platforms, where individuals connect and share personal data, have emerged as potential sources for mental health detection. This study explored the use of computational models to identify individuals with depression based on Twitter posts. We retrieved and cleaned 1.6 million tweets using Natural Language Processing (NLP) techniques for feature extraction. The Grey Relational Grade (GRG) technique was applied to investigate the association between likes and shares of Twitter posts. Furthermore, the significant values of GRG in both cases, when data is limited and when data is large, represent that GRG provides better results at large data sets. The equal distribution and selection approach (EDSA) can extract a small sample to describe the large data set and apply the GRG technique. Subsequently, we applied various machine learning models to classify user tweets into "stressed" or "not stressed" categories. These models achieved promising results, demonstrating high accuracy, precision, recall, and F1-score. Specifically, Logistic Regression, Support Vector Machine, XGBoost Classifier, and Random Forest Classifier yielded accuracies of 96, 95, 96, and 97%, respectively. These findings suggest the potential of social media data and computational models for mental health detection, thus opening avenues for further research and development.

1. Introduction

The term "social media" covers various online platforms facilitating speaking and visual communication among users. The widespread proliferation of social media, exemplified by platforms such as Twitter that link millions of people daily, provides a distinctive perspective into individuals' thoughts and feelings. Research findings suggest that a significant majority of young people. Specifically, over 92% regularly participate in social networking platforms. These individuals often use these venues to articulate their emotions and encounters, especially those about mental well-being (Keles et al., 2020). The extreme use of

social media has been associated with depression in younger populations despite its potential as a helpful tool for fostering social ties (Kim et al., 2020). The increasing need for innovative approaches to depression diagnosis presents a significant challenge to the scientific community. This study addresses this issue by proposing the application of the Grey Relational Grade (GRG) method to compare metrics, such as likes and shares, with depressive content. To the authors' knowledge, this is the first study to employ GRG in this specific domain. The GRG method offers several advantages over traditional correlation techniques, including capturing non-linear relationships and improving interpretability.

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Here, a prompt and precise diagnosis is necessary for depression, a crippling mental illness impacting almost 450 million individuals globally (Coyne et al., 2020). The task has posed difficulties due to the lack of dependable diagnostic tests (Yang & Mu, 2015). Existing studies predominantly utilize machine learning models but often overlook engagement metrics and their interrelationships. This study addresses these methodological gaps by integrating the Grey Relational Grade (GRG) method with machine learning classifiers, offering a novel, non-invasive approach to mental health diagnostics. But new AI developments like deep learning and machine learning, provide great potential for processing and extracting insights from complicated data sources like social media postings. This paves the way for promising new approaches to the non-invasive and effective identification of mental health issues, such as depression, which will provide much-needed relief to those who suffer from this common but often unspoken disease (Su et al., 2020).

This paper introduces a novel approach that combines the Grey Relational Grade (GRG) method with machine learning classifiers for classifying depression-related content. The adaptability of GRG to both large and small datasets demonstrates its potential as a comprehensive solution, addressing challenges that remain unaddressed in existing literature. Furthermore, in this study, Twitter is the information center, and our decision is based on tweets, which are short messages limited by the 140-character limit. We apply logistic Regression, XGBoost classifier, Random Forest, and Support Vector Machines classifier to recognize depressive tweets showing sadness and enthusiastic infirmity (Lin et al., 2017) see Fig. 1.

1.1. Literature review

Sisk's (1975) appraisal study predicted mental illness using data pre-processing word encoding and word embedding, models word embedding go synchronization, and used the model CNN with Lin et al. (2014) built a machine learning methodology to judge mental health symptoms second, make a validated index of collective mental well-being methodology in various campuses, investigate relationships, and use a logistic regression model and found 97% accuracy. De Choudhury (2013) used Linguistic Inquiry word count neural language processing (NLP) support vector machines (SVM), and classification accuracy is 82%. Schwartz et al. (2013) suggested that depression is low

mood, poor intention, no interest in an enjoyable environment, and no participation in daily responsibility. He used the N-gram modeling and regression model for the detection of depression. KVTKN and Ramakrishnu (2022) studied stress detection from Tweet- and user-level perspectives. They extracted a range of attributes, including language, for analysis. Visual and social attention features were derived from the attendance lists in the text, images, and individual tweets. For user-level analysis, they considered weekly tweet collection. They employed a variety of machine learning models, including logistic Regression, support vector machines, random forest, gradient-boosted decision trees, deep neural networks, factor graph models, and Convolutional Neural Networks, to assess the accuracy of stress detection (Yang et al., 2017).

Joshi et al. (2018) extracted the information from Twitter user profiles and tweets. Every Twitter user is linked with 14 attributes. These attributes also provide information related to their friends and followers and links to other users' tweet times when users re-tweet hashtag answers and use emotions the user appreciates. The author performs data pre-processing, a stop word remover, and mathematical modeling using traditional machine learning algorithms, such as the vector space model (Yang et al., 2017). The recognition of depression uses different models, such as the deep convolutional neural model visual multi-modal and deep neural network model global features with dynamic information, which is then fed into the DNN to predict the phq-8 and determine the depression on different social media and show accuracy according to the model (Xu et al., 2024).

Lin et al. (2014) stated that stress is a fundamental driver of numerous medical and mental illnesses. Constant pressure builds the danger of creating medical conditions such as sleep deprivation, heftiness, heart illnesses, malignancy, etc., and the connection between stress and mental illnesses such as nervousness problems and discouragement stress has been a danger to human well-being for quite a while frame. It is critical to distinguish and oversee pressure before it is transformed into extreme use. Existing pressure recognition strategies mainly depend on mental scales or physiological gadgets, making the location confounded and exorbitant. They investigated the natural distinction of people's mental pressures using web-based media. Utilizing genuine online miniature blog information, explore the connections between clients' pressure and their tweeting content, social commitment, and standards of conduct utilizing convolutional neural network (CNN) and deep neural network (DNN) models and cross-auto encoders.

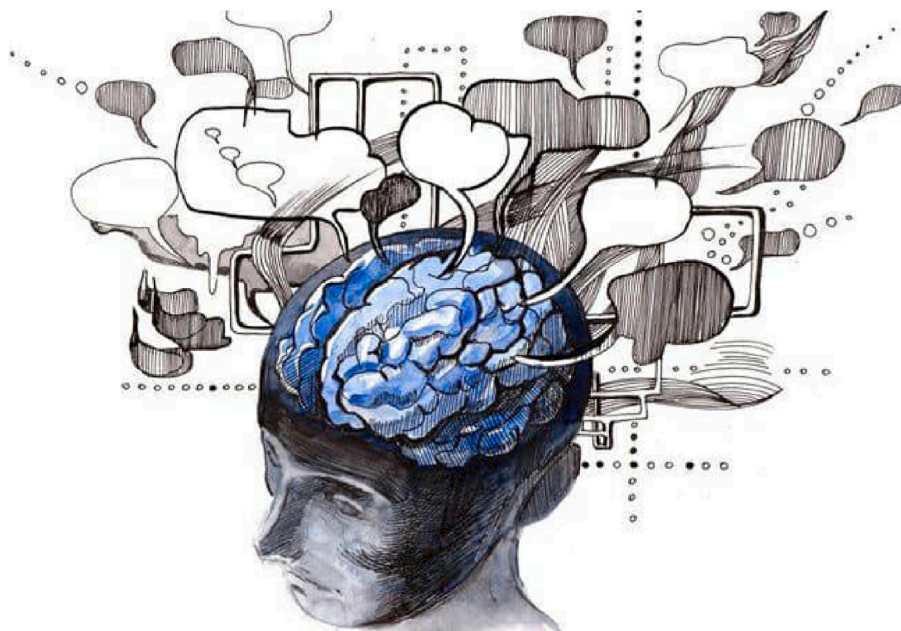


Fig. 1. Mental illness.

De Choudhury (2013) found that mental disturbance and other mental diseases are dangerous and worldwide problems in our society today. Each year, 10 million people suffer from issues such as depression and other mental illnesses, and only a few receive complete treatment. Social networking has become a common aspect of our daily lives in recent years. Facebook and Twitter are popular media platforms for sharing information. For instance, Pearson or other correlation-based methods do not capture the underlying structural form in engagement metrics (e.g., likes and shares).

Users on social media not only intercommunicate limited messages today, but most other sites are also used for sharing their images, posts, and feelings on multimedia, such as Pinterest or video Tumbler, and other media that provide the material to detect mental illness. In recent years, these technologies have become the leading causes of depression and mental illness. Tsugawa et al. (2015) argued that depression has become recognized as a common mental health problem around the world. A large number of people with depression is considered to be a severe problem. Suicide of young people is mainly caused by depression. Bagroy et al. (2017) took into account social media as a promising resource for user's fitness. By leveraging Twitter user posts to develop a predictive model on childbirth's impact on mothers' behaviors and moods, identify different illnesses using users' emotional postings, and social sites, and utilize a logistic model to forecast these symptoms.

Bagroy et al. (2017) argued that social media is a popular place for data collection, and text analysis's detection of mental illness has focused chiefly on Twitter's despair detection. While logistic regression models are effective in certain contexts, they encounter limitations when applied to large datasets and struggle to capture non-linear patterns, such as those found in social media conversations. This highlights the necessity of employing more robust methods, such as the Grey Relational Grade (GRG) technique, to address these gaps in Social Media Health (SMH) research. GRG's ability to handle complex, non-linear relationships makes it a suitable alternative for improving the accuracy and reliability of depression detection in dynamic, large-scale social media data.

Shen and Rudzicz (2017) created a sizeable statistical set of regular and anxiety-associated posts and used n-gram language vector embedding topic analysis to distinguish post-related hysteria correctly. However, N-gram models fail to consider all the essential connections within the user engagement data in terms of depth and complexity, which is even worse if one has to analyze an enormous amount of information with high levels of noise and variance. For instance, traditional models such as Pearson correlation are limited in their ability to capture non-linear relationships in engagement signals, such as likes and shares.

In contrast, this study employs the Grey Relational Grade (GRG) method, effectively addressing common challenges associated with small sample sizes, noisy data, and non-linearity. By focusing on the proximity between engagement metrics and depressive content, GRG facilitates the development of more robust and accurate stochastic models. This integration allows for a deeper understanding of user engagement behaviors and their relationship with depressive content, leading to enhanced model performance in depression detection.

1.2. Relationship between shares and likes using GRG

Twitter-like services are now a popular online social networking service where users can express themselves, share content, and follow others they are interested in. Yang et al. (2011) focused on data selection for user modeling in Twitter-like services. Kharde and Sonawane (2016) focused mainly on sentiment analysis of Twitter data, which helps analyze the information in tweets where opinions are highly unstructured, heterogeneous, and either positive or negative, or neutral in some cases. Using various machine learning algorithms, such as naive Bayes, maximum entropy, and support vector machines, Kharde and Sonawane (2016) studied Twitter data streams. We have also discussed general challenges and applications of Sentiment Analysis on Twitter. However,

few studies have examined Twitter (now called X) from a grey relational perspective. Emotions can be particularly manifested through engagement metrics, such as likes and shares, which may serve as indicators of depression. The frequency of likes and shares on depressive content exhibits a statistically significant positive correlation with the level of emotional identification with the content. This relationship suggests a potential link to depressive tendencies. GRG is a critical non-parametric correlational metric of the grey relational analysis model of the Grey System Theory, an emerging area of research within artificial intelligence (Javed et al., 2022); however, it has rarely been applied to these problems. During the literature review (Hu and Xie, 2024), the investigation of the association between likes and shares using grey relational grading (GRG) has been neglected until now. This study utilizes GRG to capture the complex and often non-linear relationship between engagement metrics and depressive content, offering a more nuanced understanding of user behavior that could indicate underlying mental health issues such as depression.

Delcea and Cotfas (2023) recently argued for using GRG-based analysis in public opinion assessment. Considering this research gap, this study attempted to extract this association using GRG. The Grey Relational Grade (GRG) method models non-proportional patterns by assessing the degree of relational closeness rather than dependency. Unlike traditional methods such as word embeddings, Pearson correlation, or Spearman correlation, GRG provides a non-parametric data normalization and proximity analysis approach. This capability enables the effective processing, filtering, and analysis of noisy, unstructured social media data, making it highly suitable for complex datasets.

If $X_S = (x_S(1), x_S(2), \dots, x_S(n))$ is the data set representing the number of shares and $X_L = (x_L(1), x_L(2), \dots, x_L(n))$ is the data set of same length representing number of likes, then Deng's GRG is given by (Javed et al., 2022; Liu et al., 2017),

$$GRG_{SL} = \frac{1}{n} \sum_{j=1}^n \frac{\min_L \min_j |x_S(j) - x_L(j)| + \xi \max_L \max_j |x_S(j) - x_L(j)|}{|x_S(j) - x_L(j)| + \xi \max_L \max_j |x_S(j) - x_L(j)|} \quad (1)$$

where ξ is the distinguishing coefficient whose value in the current study was assumed to be 0.5; before the application of GRG to the data, the data were normalized using the initializing operator (Liu et al., 2017).

Before analyzing the association between likes and shares through the GRG, it would be plausible to investigate the accuracy of the data, which the Google CoLab notebook has examined. This study used secondary data from 52542 entries extracted from [kaggle.com](https://www.kaggle.com). The accuracy of the overall dataset was 98.17%, and it was extracted using machine learning coding. We then extracted the GRG value when $n = 52542$ and found a significant value, i.e., 0.9736. A plethora of literature reveals that grey analyses seem better even for limited data (Liu et al., 2017). However, this is the first study that deployed the GRG technique on large data samples to the best of our knowledge and found significant results. Considering the limited data set approach, we aggregated the entries by dividing the total data by 500, e.g., $52542/500 = 105.084$, to apply the GRG technique on limited data. Therefore, by following the Equal Distribution and Selection Approach (EDSA), we selected the 105 entries from the raw data representing the nature of the overall data set. Subsequently, a dataset containing 105 data points is obtained, and after applying the GRG technique, we also found a significant GRG value, i.e., 0.9436. This shows that grey analyses would be better on large data sets; meanwhile, the small data set representing the overall data set also provides significant results. The results obtained using Equation (1) to these two datasets are as follows:

$$GRG_{(n=52542)} 0.9736$$

$$GRG_{(n=105)} 0.9436$$

GRG >0.8000 was generally considered significant. However, all GRG values are substantial; thus, the strong relationship between the number of shares and the number of likes is highly plausible.

1.3. Motivation and contribution

Millions of individuals worldwide suffer from debilitating depression, and this study aims to develop quicker and more accurate methods of diagnosing the illness (Coyne et al., 2020). The inaccuracy of standard diagnostic procedures usually impedes early diagnosis (Yang & Mu, 2015). Depression diagnosis is a significant public health problem that is addressed in this study. The primary motivation for this study is the need for early-stage depression screening. Current diagnostic methods often fail to detect depression at its onset, typically identifying the condition only at its advanced stages or when symptoms show signs of deterioration. Social media platforms offer a significant advantage in this context due to their widespread availability and the vast amount of data they generate. While effective in clinical settings, traditional diagnostic methods are not suited for analyzing social media engagement metrics such as likes and shares. The Grey Relational Grade (GRG) method was specifically chosen for its potential to fill this gap by providing a novel, non-linear approach to capturing user behavior patterns. A key strength of GRG is its ability to uncover additional correlations that conventional machine learning algorithms may overlook, enhancing the sensitivity and specificity of early depression detection.

Machine learning classifiers are highly effective algorithms designed for classification tasks, enabling the organization of data points into predefined categories. However, previous research has largely overlooked the interrelations among engagement metrics, leaving a critical gap in understanding depression-related behaviors. This study aims to bridge this gap by integrating social media post features with machine learning classifiers enhanced by Grey Relational Grade (GRG) analysis to achieve higher accuracy in identifying individuals with depression.

Early and accurate diagnosis is essential for timely intervention, and the proposed method offers a non-invasive, user-friendly alternative for individuals who may face barriers to conventional diagnostic techniques. This approach leverages latent features within the vast amounts of social media data, identifying patterns that are not immediately apparent but can be effectively captured through advanced computational methods. Furthermore, this study demonstrates that GRG analysis enhances scalability, making it adaptable to both large and small datasets, thereby increasing its utility in addressing public health challenges related to mental health diagnostics.

1.4. Structure of the study

The linked work is introduced, outlines differences, evaluates every study cluster, identifies the key features, and discusses particular research obstacles in Section 1. The content and methodology are explained in Section 2. The result and discussion in section 3 presents and summarizes the outcome. Comparative analysis is explored in Section 4. The article's conclusion is provided in Section 5.

1.5. Logistic regression

In 1958, a logistic regression classifier was developed for binary classification issues and predicted yes or no outcomes through machine learning (Jain et al., 2019; King et al., 2022). We use logistic regression to predict whether users have depression using two variables, x , and y . Equation (2) provides the best results for our dataset.

$$f(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}, \beta_0 + \beta_1 x = y \quad (2)$$

This equation uses the depressed case probability of dependent variable x , $f(x)$ (see Fig. 2).

1.6. Support vector machine

Support vector machines (SVM) are supervised machine-learning algorithms developed by (Tong et al., 2022; Yang et al., 2021). Most linear and nonlinear classification tasks use support vector machines. SVM uses kernel tactics, including polynomial kernel, Laplace kernel, hyperbolic tangent, and sigmoid kernel with the kernel linear classification problem and hyperplane used by the support vector machines. According to Sun and Qu (2022), the model uses kernel tricks to accomplish this classification. Kernel tricks include projecting input data into a higher-dimensional feature space to help with more successful class separation (see Fig. 3). The purpose of the text classification system in this research is to accurately identify which of many specified depression categories a particular tweet belongs to.

1.7. Random forest classification

According to Joachims (2002), the random forest (RF) method is a classification technique that constructs a decision tree and many

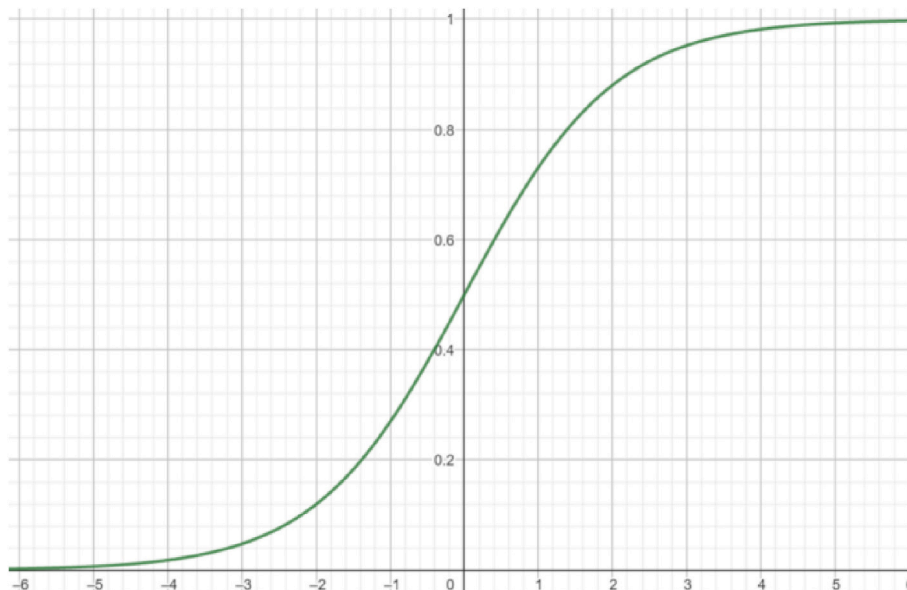


Fig. 2. Logistic regression.

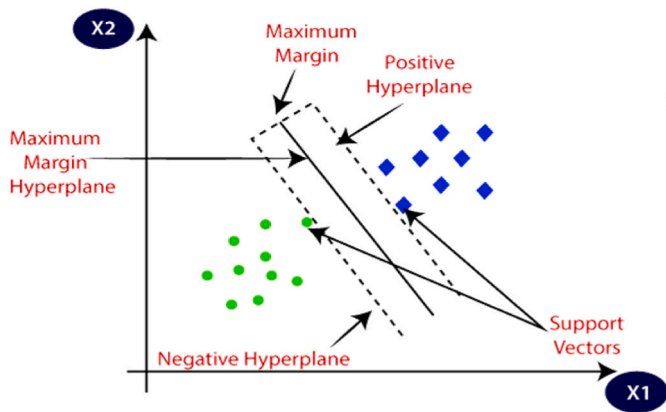


Fig. 3. Support vector machines.

independent subtrees. The construction of sub-decision trees involves bagging and randomization techniques, which yield an imbalanced forest of trees that exhibits superior identification accuracy compared to individual trees (Tong et al., 2022). The bagging technique employs bootstrap sampling to construct several decision trees from the initial sample set. The partitioning process at each node involves randomly chosen attributes from the original collection (Tong et al., 2022). The core component of any tree algorithm is the node. Notch. RF lessens the possibility of overfitting results when a single decision tree model is used (see Fig. 4).

1.8. XGB classifier

The XGB classifier is a distributed gradient boosting algorithm (Tong et al., 2022) used for supervised machine learning problems (Shen & Rudzicz, 2017). It uses gradient-boosted decision trees for speed and performance (see Fig. 5).

1.9. Aims

In this study, we set up the detection, identification, and prognosis of

separate Twitter posts, hereafter referred to as tweets, using only those tweets. The study presents a new approach that uses Grey Relational Grade (GRG) and machine learning classifiers for analyzing content related to depression. Due to its implementation flexibility with big and small data sets, GRG offers a scale-up solution to work, which is missing in current studies. We intend to lay out and put in force a computerized computational classifier capable of working in parallel on the overall performance and precision of the involved tweet. The feasibility of these computerized predictions can be cross-validated using Precision, Recall, and F1 scores.

2. Methods and techniques

Each machine-learning exam starts with data collection from several sources. Twitter is the best social media platform for public health research data, and this study uses Twitter to investigate User Tweets. This section covers Twitter user data streaming and categorizing it into training and testing datasets. In this study, we collected data from Twitter and selected tweets with symptoms of depression (Bagroy et al., 2017).

2.1. Data collection

Once the GRG has confirmed that the number of shares and likes has a significant correlation, we begin collecting data to apply the four classifiers. We collected 1,600,000 tweets using the Twitter API to train and test data sets. We collected tweets with and without stress words and extracted user ID, posting date, user type, and tweet text. Training and testing were used at 60:40 to split the data. After data collection, different pre-processing analyses were performed using NLP.

2.2. Data pre-processing

2.2.1. Data pre-processing procedure

Our analysis framework data pre-processing using an NLP task (Shen & Rudzicz, 2017). Data pre-processing is a crucial step in improving the accuracy of depression detection models by addressing issues such as duplication, noise, and irrelevant data. This process ensures that the

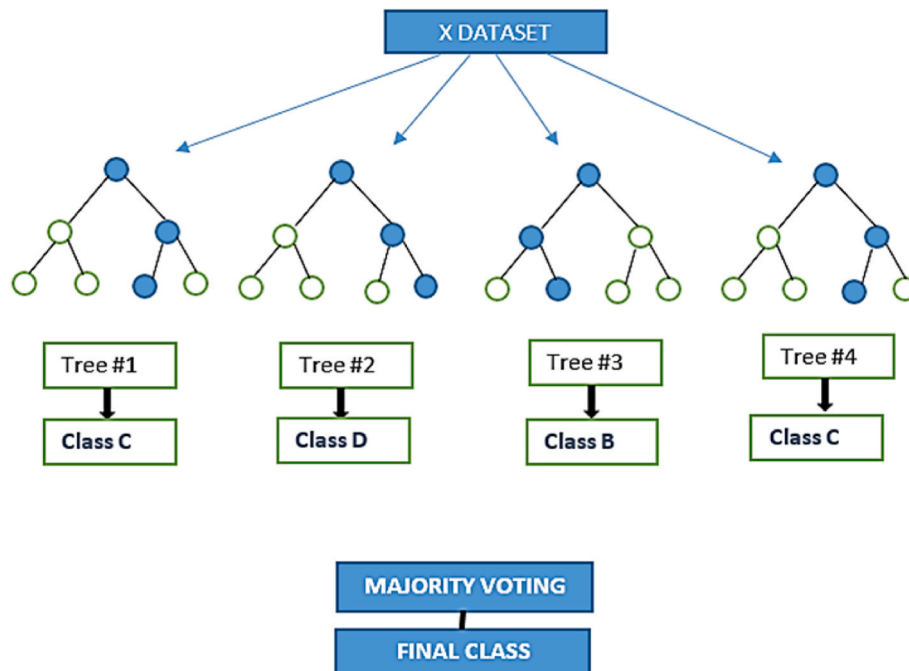


Fig. 4. Random Forest classifier.

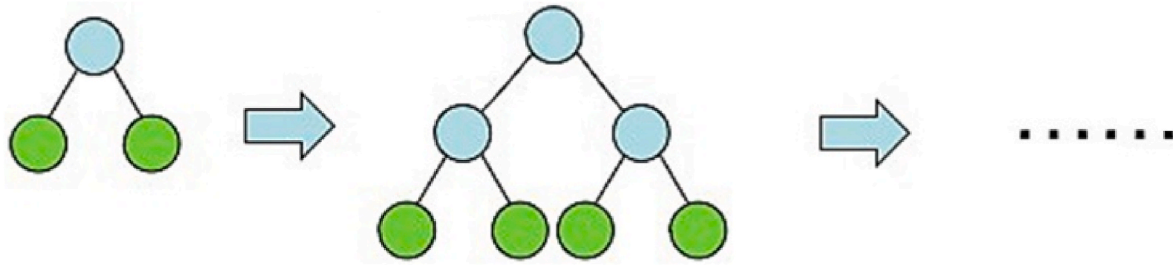


Fig. 5. XGB classifier.

data fed into machine learning algorithms is clean, free from unnecessary noise, and optimally prepared for analysis. In particular, it corrects for redundancy and irrelevant information that could compromise feature selection and model performance. Since speech signals are often noisy and may contain extra elements, pre-processing is essential for removing these distortions. This step typically involves normalizing the dataset, filtering out irrelevant content (such as non-essential URLs), and eliminating redundant data. By ensuring that only meaningful features are extracted, data pre-processing enhances the model’s ability to detect depression accurately and improves overall performance. The preprocessing is completed through the following steps:

- unnecessary words,
- post punctuations,
- hashtag,
- unnecessary URL links,
- duplicate tweets

2.2.2. Removing stop word

Stop-words are text noise; pre-processing requires filtering away unnecessary material. Since the Nltk Payton library has a list of stop words, we used it to remove them from our tweets (Jain et al., 2019). Stop words are words with no meaning in our dataset, such as "the," "an," and "is". The elimination of stop-words helps to enhance the model regarding the identification of depressive language characteristics due to the content density of terms used in the analysis given in Table 1.

2.2.3. Data subsetting with EDSA

The Equal Distribution and Selection Approach (EDSA) was implemented to optimize sample size for computational efficiency while preserving the statistical integrity of the dataset. From an initial population of 1,600,000 tweets, EDSA facilitated the selection of population subsets that enhanced the efficiency of data quantification during GRG analysis. For example, a subset of 105 tweets was extracted from 52,542 entries, maintaining consistent GRG values (full dataset: 0.9736; subset: 0.9436). This approach significantly reduced computational overhead without compromising accuracy in subsequent analyses. The study

Table 1

Pre-processing steps.

Step	Description	Impact on Accuracy
Removing noise	Eliminate hashtags, URLs, and duplicate tweets	Reduces irrelevant data, preventing skewed results.
Stop-word removal	Filter out common, meaningless words like "this", "is", "and"	It focuses on content-rich terms and enhances feature significance.
Lexicon Normalization	Reduces words to a standard form (e.g., "connected" → "connect").	Ensures consistency, avoids redundancy, and improves text normalization.
Stemming	Converts words to their root form (e.g., "running" → "run").	Simplifies terms for better analysis without loss of meaning.
Data Visualization	Represents term frequency visually using word clouds.	Identifies dominant depressive terms and patterns.

demonstrates the seamless integration of EDSA with GRG, showcasing its simplicity and effectiveness in analyzing large-scale social media data.

2.3. Feature extraction

Extracting meaningful information from text data often involves a multi-step process. First, tokenization breaks the text into smaller units, such as words or phrases. This allows for a more detailed analysis of the individual components. Lexicon normalization addresses another type of noise by reducing words with the same meaning to a standard form; for example, "connect," "connected," and "connection" could be normalized as "connect." Derivation, another normalization technique, focuses on reducing words to their base form, such as converting "run" to "run". Finally, data visualization tools such as word clouds can represent the frequency of these processed terms, providing a clear picture of the dominant themes within the text data.

2.3.1. Tokenization

De Choudhury (2013) recommended tokenization to break up a long paragraph into words and phrases. Tokenization creates a severe group-use character. This technique separated the first column of our extracted tweet from the others.

2.3.2. Lexicon normalization

Lexicon normalization think through a different type of noise in the text. For example, connection connected, connecting words reduced to common words "connect." It reduces derivationally related forms of a word to a common root word.

Stemming: Stemming (linguistic normalization) is a natural language processing (NLP) method for reducing words to their basic form, also known as the root form.

Data visualization: Word clouds display large amounts of text. Twitter data has been analyzed using word clouds. This also helps to categorize all depressive words into a single category. The flow chart of the proposed system is presented in Fig. 6.

Fig. 7 shows a direct correlation between Negative, Neutral, and Positive behavior rates. The level of comments is displayed on the y-axis, and the x-axis displays the time in hours.

The number of positive and negative occurrences in 24 h is displayed (see Fig. 8). Positive and Negative categories are displayed on the x-axis. The number of units is 0–40000 on the display y-axis.

Fig. 9 shows all common words in the dataset. Most of the time, the words used are long. The words were going, thank, love, got, lol, now, day, time, work, know, still, etc.

Fig. 10 shows the positive words in the dataset. The most common Positive words are today, time, now, think, go, love, one, work, quote, etc.

Fig. 11 shows the Negative words that show the Negative words in the data set; the most common negative words are missing, going, wish, now, go, want, still, sad, bad, sorry, suck, etc (see Fig. 12).

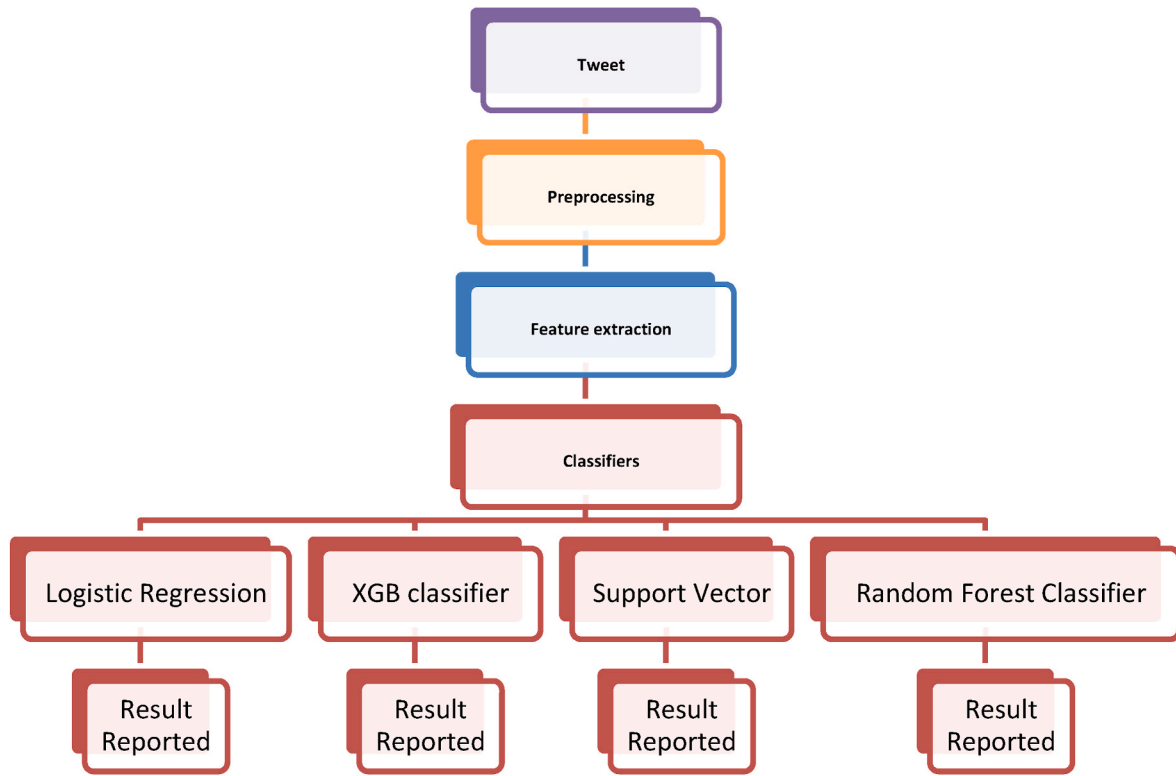


Fig. 6. Block diagram of the proposed system.

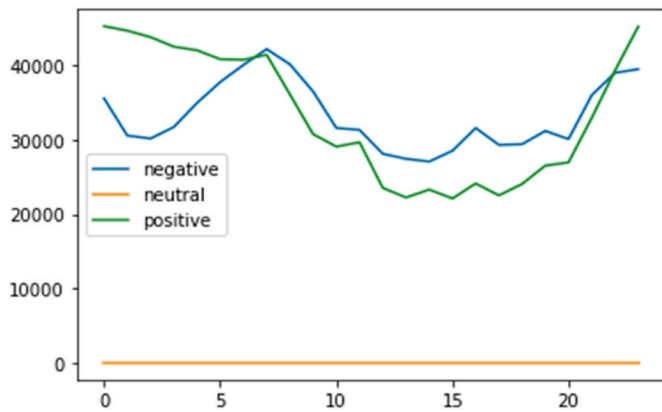


Fig. 7. Impact of negative, neutral, and positive behaviors to 24-h.

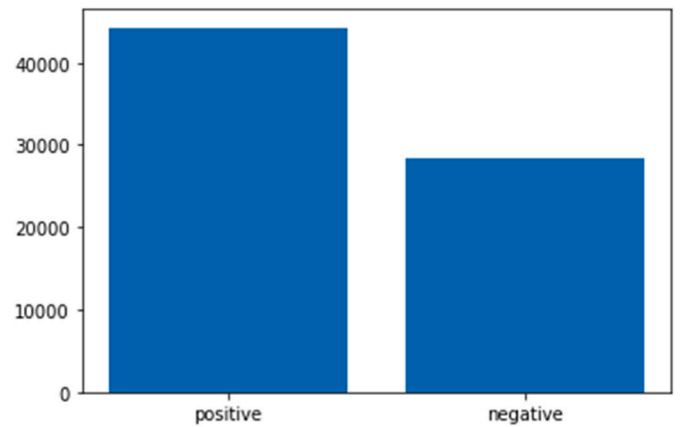


Fig. 8. Positive and negative comments.

2.4. Ethical considerations

Training depression detection models using data extracted from social media raises several ethical concerns that must be addressed to prevent misuse of the technology. Key ethical considerations include:

2.4.1. User consent and data privacy

Social media data can contain personal and sensitive information, making user consent and data privacy paramount. Obtaining explicit permission from users to utilize their data and ensuring the removal of identifiable information are critical steps. This study adhered to data ethics principles by analyzing only aggregated data and numeric summary statistics, ensuring no sensitive or identifiable information was used.

2.4.2. Minimizing harm through misclassification

Depression detection models carry the risk of misclassifying

individuals, which could lead to further harm. To mitigate this, the model was designed to balance recall and precision, ensuring accurate identification while minimizing the risks of over- or under-reporting. The goal was to achieve high accuracy without compromising the well-being of users.

2.4.3. Anonymity and data security

Confidentiality and data security were prioritized throughout the study. Stringent measures were implemented to protect personal data, and all data used were anonymized. Since the study relied solely on publicly available data from social media platforms, identifying individual users was impossible, ensuring user privacy.

2.4.4. Fairness and bias mitigation

To avoid bias and ensure fairness in the application of algorithms, it is essential to use multilingual and multicultural datasets. This study

Table 3
Logistic regression for classification results.

Precision	0.954
Recall	0.962
F1 score	0.947
Accuracy	0.962

Table 4
Random forest classifier result.

Precision	0.939
Recall	0.959
F1 score	0.959
Accuracy	0.959

Table 5
Support vector machines result.

Precision	0.963
Recall	0.961
F1 score	0.943
Accuracy	0.961

Table 6
Accuracy of models.

Classifier model	Precision	Recall	F1 score	Accuracy
XGB Classifier	0.963	0.960	0.966	0.9605
Random forest classifier	0.939	0.959	0.959	0.9592
Logistic Regression	0.954	0.962	0.947	0.9628
Support vector machines	0.963	0.961	0.943	0.9619

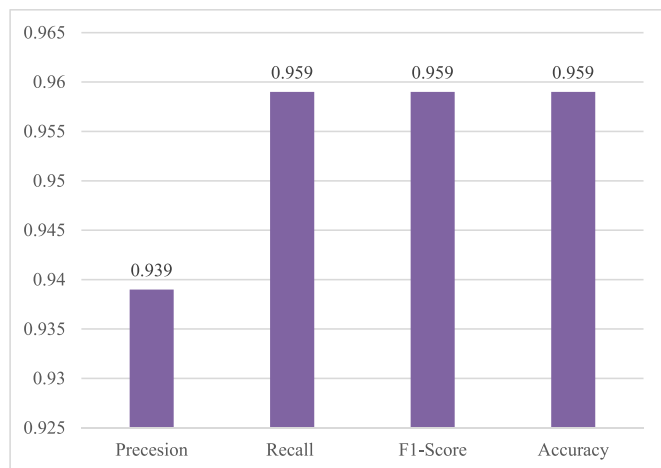


Fig. 13. Logistic Regression for Classification results.

94.3%, precision of 96.3%, recall of 96.1%, and accuracy of 96.1%, presented in Table 5.

The graphical presentation of the results using support vector machines is given in the following Fig. 15.

Future research will focus on extending the proposed framework to multimedia-rich platforms such as Facebook and Instagram by incorporating multimodal feature extraction techniques. Convolutional Neural Networks (CNNs) will be utilized for processing image data, while transformer-based models will be employed to analyze lengthy textual content (Jia et al., 2022). Multilingual embeddings such as mBERT will be integrated to enhance generalizability across linguistically diverse populations. Additionally, translation pipelines will be

incorporated to facilitate the inclusion of translated datasets, ensuring fairness and robustness across various languages. One limitation of the Grey Relational Grade (GRG) algorithm is its reliance on normalized data, which requires extensive data preprocessing, thereby increasing processing time.

The framework will also be adapted to accommodate platform-specific characteristics, including variations in content length, engagement patterns, and user demographics. These adaptations improve the model’s applicability across diverse social media ecosystems. Finally, integrating advanced models such as BERT and GPT will enhance the framework’s ability to capture contextual relationships within textual data. This will significantly improve the accuracy of depression detection across multiple platforms and languages, advancing the framework’s scalability and efficacy in real-world applications.

4. Comparative analysis

To ascertain the accuracy of these classifiers, the tweets were validated based on positive, neutral, and negative sentence scores. Logistic Regression, Support Vector Machine (SVM) classifiers, Random Forest classifiers, and XGBoost classifiers were used to compare their accuracies.

Table 6 shows the accuracy of our model, which was very high. We calculated the result based on the F1 score; the accuracy primary measure of our model was the F1 score, and the secondary measure was accuracy. The table compares the performance of four distinct machine learning categorization models. The models include Support Vector Machine, Logistic Regression, Random Forest Classifier, and XGB Classifier. The assessment measures include Accuracy, Precision, Recall, and F1-score. The percentage of accurate positive forecasts is known as precision. The percentage of real positive cases the model accurately detects is called recall. The F1-score attempts to balance accuracy and recall by taking the harmonic mean of the two. The total percentage of right predictions is called accuracy.

According to Table 6, the XGB Classifier and Support Vector Machine achieve the maximum precision (0.963), while Logistic Regression achieves the highest recall (0.962). Logistic Regression gets the highest accuracy (0.9628), while the XGB Classifier achieves the best F1-score (0.966). When selecting the optimal model for a given task, it is crucial to consider the relative significance of precision and recall. The graphical representation of all the above-stated models is given in the following Fig. 16.

In addition to evaluating classifier models, Grey Relational Grade (GRG) analysis provided a valuable supplementary perspective on predictive accuracy and the relationships within the analyzed data. Benchmark classifier models, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGB Classifier, were assessed using Precision, Recall, F1-score, and Accuracy metrics. Among these, the XGB Classifier achieved the highest F1-score of 0.966, indicating a balanced performance between precision and recall. Logistic Regression demonstrated superior performance in Recall (0.962) and Accuracy (0.9628). Supporting this evaluation, GRG analysis was employed to examine the relationship between likes and shares across datasets of varying sizes. For the full dataset, the GRG value was calculated at 0.9736, indicating a strong positive correlation. A subset of 105 randomly selected records yielded a GRG value of 0.9436, which remains significantly above the standard threshold of 0.8000. These findings highlight the robustness of GRG analysis in capturing relational insights. When used in conjunction with advanced classifier models like the XGB Classifier, which excels in handling complex data associations, GRG analysis enhances the understanding of intricate relationships within the dataset. Together, these techniques offer a comprehensive view of data structure and predictive performance, reinforcing their utility for advanced analytics.

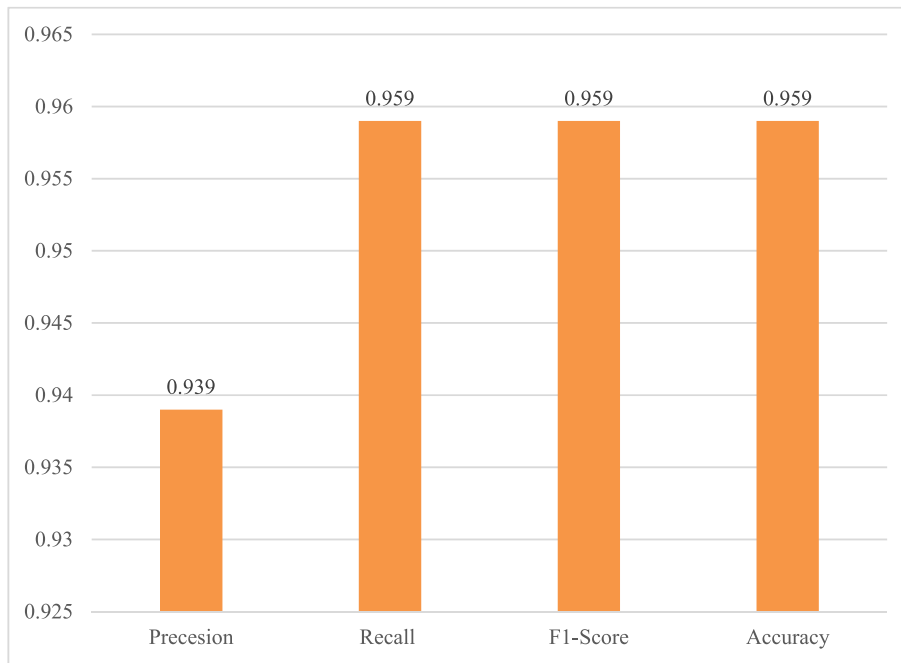


Fig. 14. Random forest classifier result.

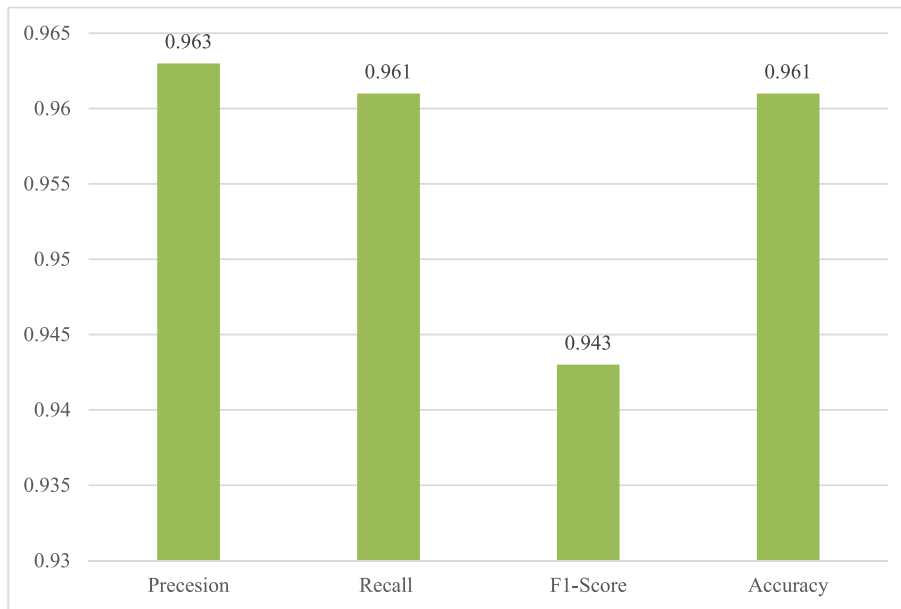


Fig. 15. Support Vector Machines result.

5. Conclusion

With this new level of detail, we may be able to understand people’s mental health conditions better and devise more effective treatments. In addition, there is great promise for providing instant support and help to persons suffering from depression by cultivating an efficient and accurate framework that functions in real-time. The potential for social media data to be used effectively in mental health diagnosis and assistance might be realized with further research, careful consideration of ethical issues, and close cooperation with healthcare providers. Possible directions for future research include (1) expanding the current binary system of mental health labels to include more nuanced categories and (2) investigating the feasibility of a real-time intervention framework that takes advantage of the instantaneous nature of social media to offer

direct assistance and resources to people battling depression. These innovations may one day make mental health diagnosis and treatment much more efficient in the modern day. In addition, GRG’s statistically significant values in both the small and large data sets indicate that GRG excels while working with big datasets. To apply the GRG approach to a big data set, EDSA may extract a tiny sample representing the complete set. To apply the GRG technique, EDSA can extract a small sample to represent the large data set.

CRedit authorship contribution statement

Wusat Ullah: Writing – review & editing, Writing – original draft, Validation, Software, Resources, Investigation, Formal analysis, Data curation, Conceptualization. **Patrícia Oliveira-Silva:** Writing – review

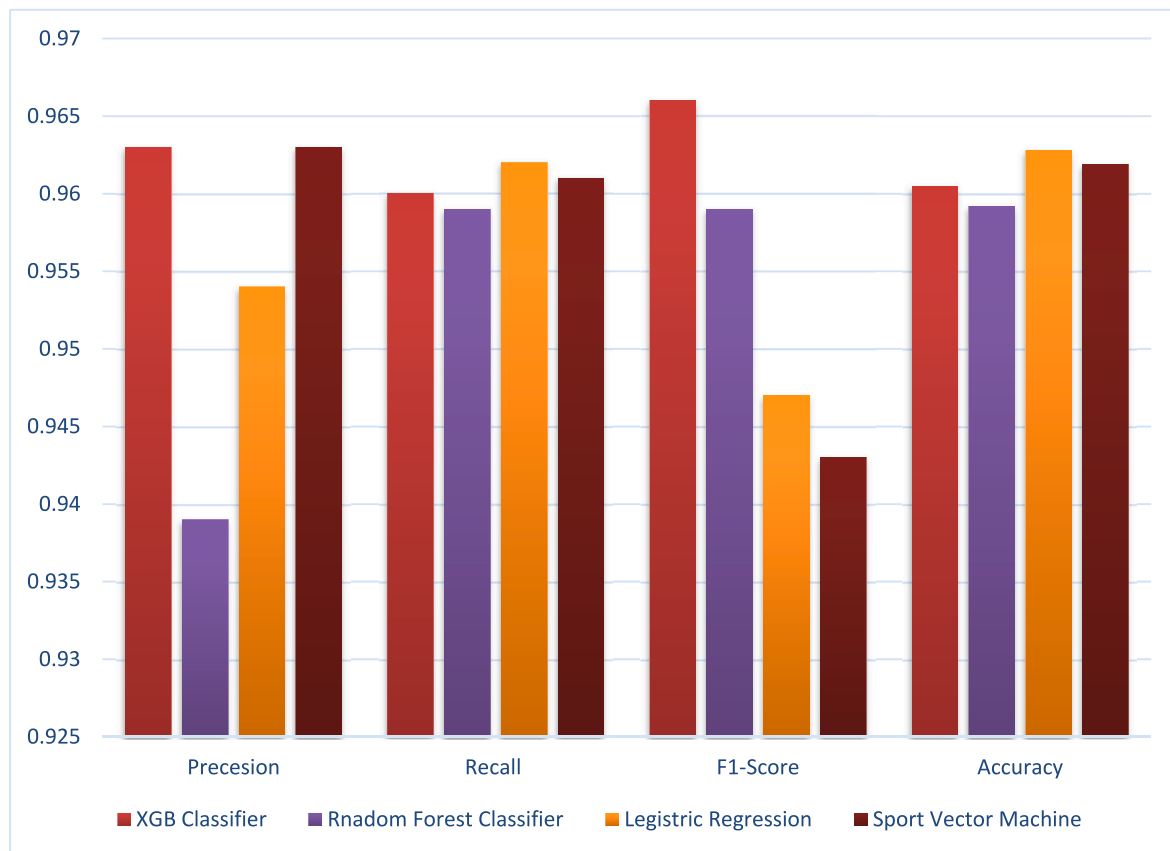


Fig. 16. Comparative analysis of different models.

& editing, Visualization, Validation, Supervision, Project administration, Investigation, Funding acquisition. **Muhammad Nawaz:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Formal analysis, Conceptualization. **Rana Muhammad Zulqarnain:** Writing – review & editing, Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Imran Siddique:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation. **Mohammed Sallah:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Data availability

Data is available from the corresponding author upon reasonable request.

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