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RESEARCH ARTICLE

Novel Transformer Based Contextualized Embedding and Probabilistic Features for Depression Detection From Social Media

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ABSTRACT Depression constitutes a significant mental health condition, impacting an individual's emotional state, thought processes, and ability to carry out everyday tasks. Depression is defined by ongoing feelings of sadness, diminished interest in previously enjoyed activities, alterations in hunger, sleep disturbances, decreased vitality, and challenges with focus. The impact of depression extends beyond the individual, affecting society at large through decreased productivity and higher healthcare costs. In the realm of social media, users often express their thoughts and emotions through posts, which can provide insightful data for identifying patterns of depression. This research aims to detect depression early by analyzing social media user content with machine learning techniques. We have built advanced machine learning models using a benchmark depression database containing 20,000 tagged tweets from user profiles identified as depressed or non-depressed. We are introducing an innovative BERT-RF feature engineering method that extracts Contextualized Embeddings and Probabilistic Features from textual input. The Bidirectional Encoder Representations from Transformers (BERT) model, based on the Transformer architecture, is used to extract Contextualized Embedding features. These features are then fed into a random forest model to generate class probabilistic features. These prominent features aid in enhancing the identification of depression from social media. In order to classify tweets using the features derived from the BERT-RF features selection step, we have used five popular classifiers: Random Forest (RF), Multilayer Perceptron (MLP), K-Neighbors Classifier (KNC), Logistic Regression (LR), and Long Short-Term Memory (LSTM). Evaluation experiments show that our approach, using BERT-RF for feature engineering, enables the Logistic Regression model to outperform state-of-the-art methods with a high accuracy score of 99%. We have validated the results through k-fold cross-validation and statistical T-tests. We achieved 99% k-fold accuracy during the validation of the proposed approach. This research contributes significantly to computational linguistics and mental health analytics by providing a robust approach to the early detection of user depression from social media content.

INDEX TERMS Depression detection, machine learning, deep learning, text mining, BERT, transformer.

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I. INTRODUCTION

Depression is a complex mental health condition that affects an individual's emotions, cognition, and daily functioning [1]. Characterized by more than transient sadness or a challenging period, it manifests as a persistent sense of melancholy, diminished interest or pleasure in previously enjoyed activities, and a variety of intense and enduring physical and emotional symptoms. These symptoms can differ among individuals, typically encompassing persistent sadness, a marked loss of interest or pleasure, and notable changes in diet or weight [2], among others. The etiology of depression is multifaceted, involving genetic, biological, environmental, and psychological factors. Additionally, trauma, stress, significant life alterations, certain medications, and pre-existing medical conditions can precipitate its development [3]. Effective management of depression often requires a comprehensive approach, including therapy, pharmacological treatment, lifestyle modifications, and support networks, which can significantly mitigate symptoms and improve quality of life [4].

Treating depression often involves a multifaceted approach tailored to the individual. Preventing depression necessitates a proactive stance towards mental health. Regular exercise, healthy nutrition, and adequate sleep form the cornerstone of maintaining a sound and resilient mind [5]. Depression is a mental illness that can cause significant disruptions across all facets of life. It extends beyond sadness, impairing daily functioning through diminished cognitive abilities and decision-making capacities. In severe cases, it can escalate the risk of suicidal thoughts or behaviors [6]. Addressing depression effectively requires a comprehensive strategy that includes professional support, therapy, medication, lifestyle adjustments, and motivational encouragement.

The prevalence of depression can vary by population and region, with data subject to change over time due to numerous factors, including shifts in diagnostic criteria, advances in knowledge, and societal changes [7]. Despite these variations, depression remains a significant global mental health challenge. Recent updates, as of 2022, indicate that the incidence of depression has been on the rise over the years. The World Health Organization (WHO) identifies depression as the leading cause of disability worldwide, impacting over 264 million individuals across various age groups as reported in 2020 [8]. The significance of early intervention cannot be overstated, highlighting the need to diminish stigma, enhance access to mental health services, and increase awareness about this issue. However, while these traditional approaches are cost-effective, there is an emerging need for advanced machine-learning approaches for the early detection of depression through social media analysis.

Social media platforms have presented an unparalleled chance to examine mental health disorders, such as depression, on a significant scale. Twitter has become a wonderful resource for gaining insights into people's thoughts and emotions. Twitter users frequently disclose their personal experiences, sentiments, and emotions, enabling the examination and detection of indications of depression in their public messages.

Advanced machine learning-based early detection of depression from social media is essential for studying depression in medicine [9]. Machine learning offers a variety of models that can be trained using accurate data to generate precise predictions. This work introduces a novel BERT-RF (Bidirectional Encoder Representations from Transformers-Random Forest) based stress detection model that improves efficiency during training and enhances the accuracy of predictions. Our new research makes significant contributions in the following areas:

- We proposed a novel BERT-RF feature engineering approach that extracts Contextualized Embeddings and Probabilistic Features from textual data. First, the Transformer architecture-based BERT extracts Contextualized Embedding features, which are input into a random forest model for generating class probabilistic features. These salient features help to improve depression detection from social media.
- We employed four advanced machine-learning models and a deep-learning model for results comparison. We improved the performance by optimizing the hyperparameters. To validate performance, we applied k-fold cross-validation and statistical T-test analysis.

The remaining manuscript is set as Section II describes the study and is devoted to examining the limitations of the existing literature. In section III, we have described in-depth our new approach to researching depression using the best features in BERT-based content embedding and social media data. Then, in Section IV, we compare the results obtained from our study's various machine-learning methods. Finally, Chapter V details the results of our new research.

II. LITERATURE REVIEW

The global impact of depression, problems with early diagnosis, and widespread stigma in Arab culture require a new approach. Social media is researching mental health services and has recently increased interest in depression research, especially in English studies.

This study [10] conducted Arab-centered research by analyzing Twitter data from the Gulf region to detect depression. Use supervised learning algorithms such as Random Forest and Naive Bayes to build predictive models based on online depression behaviors rather than symptoms. More importantly, the model, specifically the Liblinear classifier, in this study achieved 87.5% accuracy in detecting depression tweets, demonstrating the effectiveness of this feature in capturing messages related to mental illness from Arab users. This study shows the potential of digital media to promote early detection of depression and improve cultural awareness and depression intervention in Arabic-speaking communities.

This [11] study combines deep learning with traditional machine learning techniques to distinguish normal users from abnormal users on social media profiles. This study explored extensive literature to identify mental health indicators using different media and behavioral approaches. Integrating deep

TABLE 1. The summary analysis of reviewed literature studies.

Ref.	Year	Dataset	Technique	Performance Score
[10]	2019	Dataset collected from self-reported	Random forest algorithm	87.5% Accuracy Score
[11]	2018	Dataset collected from different media and behavioral approaches	K-Neighbor	89% Accuracy Score
[12]	2019	data collect from clinical interviews	GRU	90% Accuracy Score
[13]	2021	Dataset collected from public Tweets from Twitter	Random forest algorithm	77% Accuracy Score
[14]	2022	Dataset collected from Kaggle	TF-IDF	89% Accuracy Score
[15]	2021	Data collected using the Twitter Application Programming Interface (API)	SVM Classifier	87.5% Accuracy Score
[16]	2019	Dataset collected from PHQ-9	logistic regression classifier	86.45% Accuracy Score
[17]	2022	Dataset collected from self-reported	Convolutional Neural Network(CNN)	94.28% Accuracy Score
[18]	2022	data collect from UCI	Catboost/GB model	91% Accuracy Score
[19]	2020	self from Facebook and Twitter	Random Forest Model	90.3% Accuracy Score

learning makes it more useful, especially in distinguishing normal users from abnormal users. The important thing is that this method achieves a lower error rate than traditional methods. This study achieved an accuracy rate of 89%, demonstrating the effectiveness of deep learning in the psychological analysis of social media data. This study highlights the important role of deep learning-based inference in improving psychological analysis in social media and suggests a significant increase in accuracy and dispersion.

This study [12] achieved an accuracy rate of 90%. The system has been validated by tests showing its superiority over existing systems. The proposed model showed more than a 30% reduction in errors, demonstrating its effectiveness in searching for depression in users. Various experiments and examples have confirmed the effectiveness of this model in analyzing the level of emphasis in user texts. Additionally, the model has been shown to perform well in real-world situations, confirming its effectiveness. This study highlights the importance of multi-modal collaboration in advancing depression research on social media platforms, highlighting significant improvements in accuracy and robustness in capturing content expressed in user messages.

This [13] study was diagnostic criteria are based on patient-reported symptoms and have implications for patient management; Therefore, alternative methods should be investigated. Social media platforms like Facebook, Twitter, Reedit, and Tumbler offer new ways to collect behavioral data that can reveal insights into a user's emotional state. This research focused on creating a machine learning framework to examine linguistic trends in Twitter user data for detecting depression indicators. The performance of support vector machine and random forest algorithms was evaluated and contrasted, with the random forest algorithm demonstrating superior effectiveness. This study achieved an accuracy of 77%. Machine learning models, specifically random forests, have been shown to best detect depressive symptoms based on message patterns in Twitter data.

This study [14] analyzed users' Twitter posts to determine the likelihood of depressive symptoms among online users. This study focused on using machine learning and language techniques to teach material and evaluate the plan's effectiveness. This study reports the numerical score from tweet sentiment and achieved 78% accuracy in detecting depression using the XGBoost classifier. Additionally, by combining features such as TFIDF, NGram and LDA, 89% accuracy is achieved with the support vector machine classifier. Correct selection and their combination are important factors contributing to improved performance. The findings highlight the importance of integrating emotion and speech in identifying depressive symptoms from Twitter data. This study demonstrated the effectiveness of machine learning techniques in identifying potential signs of depression in online users.

This [15] study used machine learning techniques that focus on detecting depression in Twitter users by extracting tweet features. In this study, a classification technique was used that aims to distinguish depressed users from other users by analyzing features extracted from tweets. A machine learning algorithm is used to classify the collected tweet data to detect whether the user is depressed. This study achieved an accuracy rate of 87.5%. This prediction is for early detection of depression or other mental health conditions.

This study [16] evaluated depression and suicidal thoughts according to depression level. Data collection includes a survey similar to the PHQ-9 that surveys demographic information, including current age, gender, and school attendance [20]. Based on the collected data, a classification algorithm was used to classify severe depression into five levels. The XGBoost classifier achieved an accuracy of 83.87% on this data, demonstrating the model's effectiveness. Additionally, the information collected through tweets is classified to determine whether the user is depressed. The maximum value of the logistic regression classifier for detecting depression in tweets is 86.45%.

This study [17] aims to predict users' psychological states by using deep learning models to classify depressed and non-depressive tweets. Leveraging text content and deep learning architectures, specifically CNNs and LSTMs, a hybrid model was created that achieved 94.28% accuracy on Twitter's distressed dataset. Compared to RNN, CNN, and the basic method, it can be seen that the best CNN and LSTM model in terms of prediction performance is based on different parameters. Statistical and visual methods highlight the importance of distinguishing between melancholic and non-melancholic subjects. This study used Twitter's depression data using deep learning techniques to recognize language patterns and predict users' emotional states. The findings highlight the effectiveness of the CNN and LSTM model in classifying depressed and non-depressed tweets and demonstrate its potential to improve predictive performance for assessing mental health control.

This [18] article introduces a self-report method using self-reports in tweets and proposes a new multi-modal framework for predicting depression symptoms based on user data. This study uses the n-gram language model, LIWC dictionary, automatic image tagging, and bag-of-words and adopts relationship-based selection and nine categories to measure performance. The analysis showed that tweets and texts were 91% and 83% accurate in predicting depression symptoms, respectively, yielding positive results. This study suggests that efficiency can be improved by reducing the number of users using or participating in medical records. The data was collected from the social platform focused on self-expression and user data in tweets to predict depression symptoms using various techniques and classifications. The findings highlight the effectiveness of using user-generated content, particularly tweets, to predict symptoms of depression and highlight the potential of multiple baselines in mental health assessment.

This study [19] begins with a comprehensive review of Bengali language literature on depression-related reporting and comments on social media. Machine learning methods, including support vector machines, decision trees, random forests, polynomial naive Bayes, K-nearest neighbors, and logistic regression, are used to predict depression in many ways. This study achieved an accuracy of 90.3% with TF-IDF, a Random Forest Model. Data collection focused on depression-related content in tweets and responses in Bangladesh to facilitate algorithmic prediction. Different machine learning algorithms have different predictive values; however, the accuracy of each algorithm applied to the dataset remains the same.

A. RESEARCH QUESTIONS AND GAPS

In order to demonstrate the uniqueness of our work, we presented a summary in Table 1 of the most significant distinctions that exist between the approaches applied in the current literature and the methodology that we have proposed, as well as the accuracy that has been achieved. During our literature analysis, we identified several gaps that are addressed in our proposed research approach. We propose a novel transformer-based feature engineering method, BERT-RF, which extracts contextualized embeddings and probabilistic features from textual data. This contrasts with the classical approaches predominantly used in current literature.

- Previously, researchers relied solely on the BERT model for feature representation and also deployed classical tree-based models. How can advanced features engineering and models be built for depression detection?
- The performance scores of these methods were moderate when compared to the state-of-the-art. How can high-performance scores using applied models be achieved for depression detection?

III. PROPOSED METHODOLOGY

In Figure 1, our proposed methodology process begins with the user's text message dataset. These raw data undergo a prequalification process to enhance their suitability for analysis. Preprocessing includes methods such as tokenization, normalization, and stemming. Tokenization divides the text into individual units, normalization standardizes the representation and stemming simplifies the text by reducing words to their base forms. Subsequently, the feature extraction step isolates significant information from the preprocessed data. This step involves selecting key features using the novel model proposed by BERT-RF. Following feature extraction, the dataset is split into two parts: a training set and a test set, with 80% of the data allocated to training and 20% to testing. This division allows the model to learn patterns from the training set and assess its performance on the test set, including data not seen during the training phase. We applied several advanced machine learning models. The final step involves analyzing the prediction model to draw conclusions. The results typically highlight conditions under which the model predicts depression and those under which it predicts the absence of depression. Based on their posts, this final analysis provides crucial information regarding the user's overall mental health status.

A. PHASE 1: DEPRESSION TEXTUAL DATA

This study used a benchmark depression database [21] containing 20,000 tagged English tweet user profiles of depressed and non-depressed users. The data includes important details about users such as post text, friends, followers, and social media activities. This information is stored in a data set and used as a reference for subsequent stress tests. The data set is treated according to the main features, referring to features that may indicate melancholic preferences and ignoring others represented by the content of the melancholic or non-melancholic text. By taking into account the user's history of social media posts and statements, it is aimed to increase the accuracy of the results and contribute to better results in the research of depression by psychologists.

B. PHASE 2: TEXT PREPROCESSING AND DATA ANALYSIS

Figure 2 shows that Data preprocessing is the major portion of data mining. The first method removes the user's custom text format. The objective of this technique is to eliminate elements such as "usernames (@usernames)", "hashtags (hashtags)," "URLs," "non-alphabetic characters, symbols, and digits," "blank strings," "rows containing NaN values," and "Black-line" among others. This approach ensures the

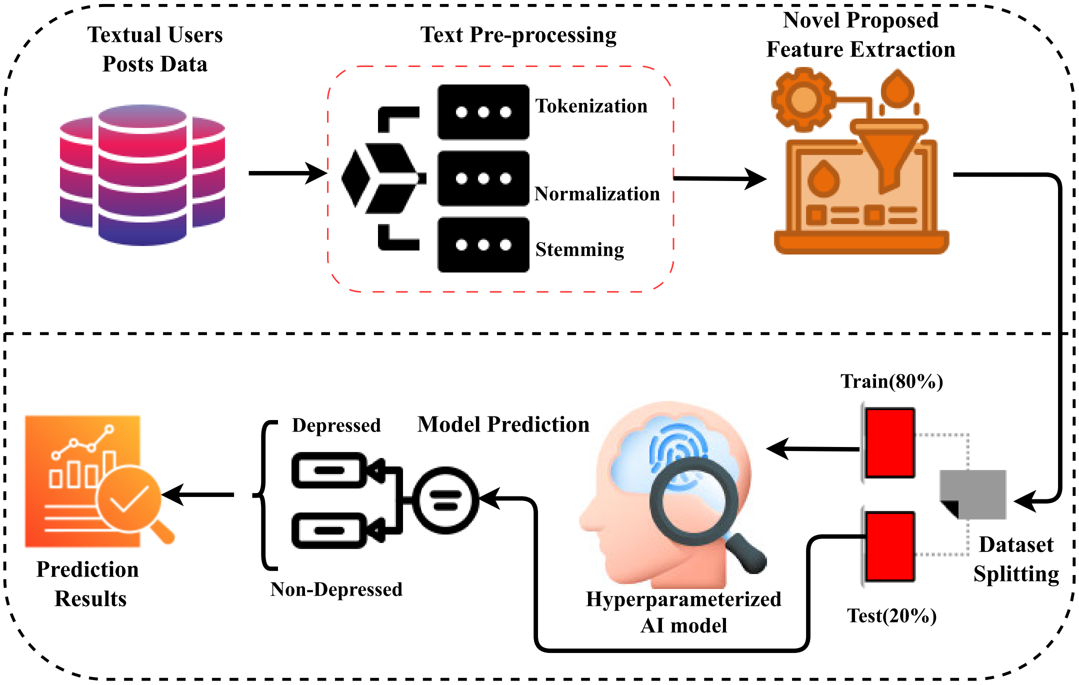


FIGURE 1. Proposed methodology workflow.

purification of each tweet in the collection by excluding all URLs present within the tweets. Subsequently, it focuses on discarding dates, times, numbers, and hashtags. The process then advances to eliminating emojis, redundant spaces, and extra spaces within sentences. Following this, the technique involves the extraction of stems through the removal of stop words, which are words like "if," "of," and "else" that do not add significant meaning to sentences. The NLTK library provides a collection of stop words to filter out these non-contributory words from the text. Stemming is employed to reduce words to their base or root form. The ultimate aim is to transform each word in a tweet into a sequence of digits, substituting them with their respective values found in a dictionary index.

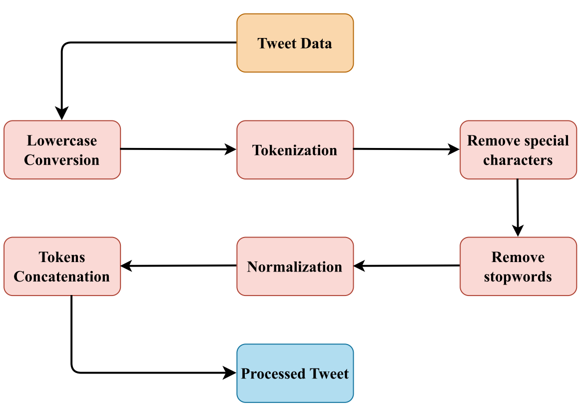


FIGURE 2. The user post text data workflow.

In deep learning, the word cloud is not used directly but has implications in the broader field of natural language processing (NLP) and text analysis, as shown in Figure 3. It works as a visual method rather than a deep learning method. A word cloud visually represents the frequency of words in text; frequently used words appear in larger letters. While not as complex as deep learning models often used in sentiment analysis or translation tasks, word clouds provide a simple and intuitive way to search for and communicate body landmarks.

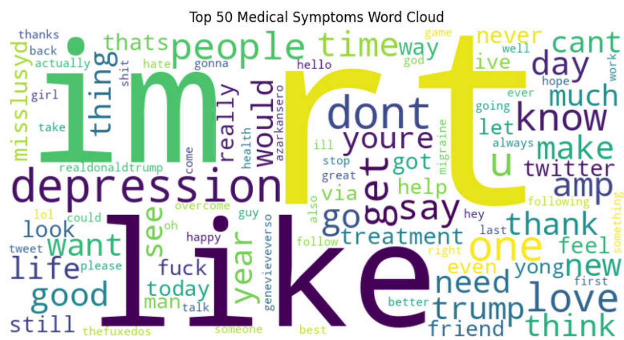


FIGURE 3. Visualizing textual patterns: A word cloud analysis.

C. PHASE 3: NOVEL PROPOSED BERT-RF TEXTUAL FEATURE EXTRACTION

In this section, we describe our novel approach to salient feature engineering. The workflow for extracting features from textual data is illustrated in Figure 4. The use of

BERT-based contextual embeddings has become a popular method in researching social anxiety. Initially, we input the preprocessed textual data into the pre-trained BERT transformer model, which generates embeddings for each token in the text while preserving context information. Features extracted from these embeddings can be selected for specific tokens or aggregated across the entire sentence [22]. To enhance the model's capabilities, we include potential features as inputs to a random forest model to generate probabilistic features. These probabilistic features are then utilized for training the models applied in detecting depression from social media. Careful interpretation and validation of predictive models are crucial, especially when addressing mental health issues.

Algorithm 1 outlines the sequential process for extracting novel features.

Algorithm 1 BERT-RF Algorithm

Input: Depression Post Textual Content.
Output: Novel Feature Set.
initiate;
1- $BERT_{ce} \longleftarrow E_{BERT}(D_t)$ // here $BERT_{ce}$ are the Contextualized Embedding features and D_t are input Textual Content.
2- $RF_{pf} \longleftarrow P_{RF}(BERT_{ce})$ // here RF_{pf} are the Probabilistic features and $BERT_{ce}$ are input Contextualized Embedding features set.
3- $F_t \longleftarrow RF_{pf}$ // here F_t are the Novel feature set.
end;

D. PHASE 4: FEATURES DATA SPLITTING

In this study, we used an 80:20 data split, with 80% of the dataset used to train the machine learning model and 20% to evaluate the model's performance. To achieve this, the data is split using the train-test-split() method in the scikit-learn module. This separation method is chosen to reduce the risk of overworking and improve the model's overall performance [23]. This study also includes k-fold cross-validation to validate the results obtained from the profile segmentation process. This data splitting helps ensure that the model's performance is measured consistently across different parts of the data set, thus increasing the reliability of the results.

E. PHASE 5: APPLIED ARTIFICIAL INTELLIGENCE MODELS

In artificial intelligence, many well-known algorithms [24] have become the backbone of solving various problems, such as depression detection from social media. Together, these AI-based models create comprehensive tools that address numerous real-world situations and allow clinicians to derive valuable insights from the data.

- **Random Forest Classifier (RF)** is a classification and regression technique that uses bootstrapping and multiple decision trees to create forests [25]. RF represents the union of prediction trees; each tree depends on the value of the selected value vector. After receiving new input data, the algorithm creates a decision tree for that data and merges it with another decision tree in the forest. The RF uses the feature vectors $\{V_1, V_2, \ldots, V_n\}$ as input to classify each post into categories such as *depressed* or *not depressed*. The prediction for a post P_i can be represented as:

$$\hat{y}_i = \mathrm{RFC}(V_i) \tag{1}$$

where the predicted classification for each post, denoted as P_i, is represented by $\hat{y}_i$. Here, a value of $\hat{y}_i = 1$ signifies that the post is classified as *depressed*, whereas $\hat{y}_i = 0$ denotes classification as *not depressed*.
The Random Forest Classifier decision function for a given post P_i can be further detailed as:

$$\hat{y}_i = \frac{1}{N} \sum_{j=1}^{N} \mathrm{DT}_j(V_i) \tag{2}$$

where N is the number of decision trees in the forest, and DT_j is the prediction of the j-th decision tree. A majority vote among all trees typically determines the final classification.

- **Multilayer Perceptron (MLP)** is a good neural network model used specifically for task classification [26]. There are many layers of connections between nodes or neurons, and the model works in a feed-forward manner, with information passing through each layer and making connections within and between layers. Let's denote the input layer by $\mathbf{x} \in \mathbb{R}^d$, where d is the number values of features extracted from social media data. The MLP consists of L layers, each with its own set of weights $\mathbf{W}^{(l)}$ and biases $\mathbf{b}^{(l)}$, where $l \in \{1, 2, \ldots, L\}$ represents the layer index.
The output of each layer l is calculated as:

$$\mathbf{h}^{(l)} = f(\mathbf{W}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}), \tag{3}$$

where f represents a non-linear activation function, like the ReLU function, which is denoted by $f(z) = \max(0, z)$, and $\mathbf{h}^{(0)}$ equals the initial layer $\mathbf{x}$.
The final output layer (assuming binary classification for depression detection, with 1 indicating depression and 0 indicating no depression) is given by:

$$\hat{y} = \sigma(\mathbf{W}^{(L)}\mathbf{h}^{(L-1)} + \mathbf{b}^{(L)}), \tag{4}$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$ is the sigmoid activation module, and $\hat{y}$ is the predicted probability of depression.

- **K-Neighbors Classifier (KNC)** utilized to classify new data based on the most common classes of nearest neighbors at a given location [27]. Calculate the distance between data points to determine proximity. K, the number of neighbors data, and the distance measure are important. Given a set of n social media posts $\mathcal{P} = \{p_1, p_2, \ldots, p_n\}$, where each post p_i is represented

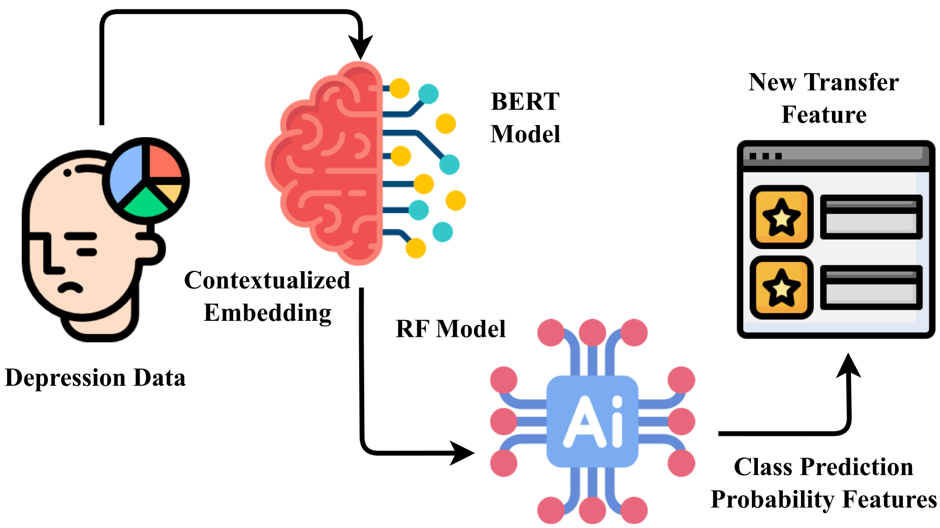


FIGURE 4. The architecture analysis of the novel proposed BERT-RF textual feature extraction method.

by a feature vector $\mathbf{x}_i \in \mathbb{R}^d$ extracted from the text, and a corresponding label $y_i \in \{0, 1\}$ indicating the absence (0) or presence (1) of depressive indicators. The K-Neighbors Classifier (KNC) method for depression detection can be described as follows:

1) For a given unlabelled post p_u with feature vector $\mathbf{x}_u$, compute the distance $D(\mathbf{x}_u, \mathbf{x}_i)$ between $\mathbf{x}_u$ and each $\mathbf{x}_i$ in the training set $\mathcal{P}$. Common distance metrics include Euclidean distance:

$$D(\mathbf{x}_u, \mathbf{x}_i) = \sqrt{\sum_{j=1}^{d} (\mathbf{x}_u^{(j)} - \mathbf{x}_i^{(j)})^2}$$

2) Identify the k nearest neighbors of $\mathbf{x}_u$, denoted as $\mathcal{N}_k(\mathbf{x}_u)$, based on the smallest distances $D(\mathbf{x}_u, \mathbf{x}_i)$.
3) Determine the majority label values among the k nearest neighbors:

$$\hat{y}_u = \arg\max_{y\in\{0,1\}} \sum_{\mathbf{x}_i \in \mathcal{N}_k(\mathbf{x}_u)} \mathbb{I}(y_i = y)$$

where $\mathbb{I}$ is an indicator values function that is 1 if $y_i = y$ and 0 otherwise.

The predicted label $\hat{y}_u$ indicates whether the post p_u is likely to exhibit depressive indicators (1) or not (0), based on the content similarity to the labeled posts in the training set.

- **Logistic Regression (LR)** uses the sigmoid function to model the probability that inputs belong to a particular class [28]. This model involves a combination of input strategies converted to a quality between 0 and 1. The basic mathematical equation of the LR model is expressed as follows:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}} \tag{5}$$

where:

-- $P(Y = 1)$ is the probability value of an individual being detected as depressed (Y=1) based on their social media activity.
-- e is the base value of the natural logarithm.
-- β_0 is the intercept term value of the model.
-- $\beta_1, \beta_2, \ldots, \beta_n$ is the value coefficients of the predictor variables $X_1, X_2, \ldots, X_n$, which represent different features extracted from social media activity, such as the frequency of posts, sentiment analysis scores, or the use of specific words related to depression.
-- $X_1, X_2, \ldots, X_n$ are the predictor variables (features) derived from social media data.

- **Long Short-Term Memory (LSTM)** networks [29] are a special type of recurrent neural network (RNN) designed to solve the missing space problem in traditional RNNs. LSTM is particularly useful for tasks that deal with continuous objects, such as time estimation and natural language processing. The key to their success is integrating brain memory, which is equipped with gates (input, memory, and output) that control the network's information flow. The input gate decides what data to store in memory, the memory gate decides what to discard, and the output gate calculates the next hidden state based on the ideas and current state of memory. The basic equations governing an LSTM unit are as follows:

-- Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{6}$$

-- Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{7}$$

-- Cell state update:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (8)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (9)$$

-- Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (10)$$

-- Hidden state update:

$$h_t = o_t * \tanh(C_t) \quad (11)$$

where:

-- f_t is the forget gate's value activation vector,
-- i_t is the input gate's value activation vector,
-- $\tilde{C}_t$ is the cell input value activation vector,
-- C_t is the cell state vector value,
-- o_t is the output gate's value activation vector,
-- h_t is the hidden state vector values (also the output vector of the LSTM unit),
-- x_t is the input vector at time step t,
-- h_{t-1} is the hidden state vector at time step $t-1$,
-- C_{t-1} is the cell state vector at time step $t-1$,
-- W and b are the weights and biases of their respective gates,
-- σ is the sigmoid function, and
-- $*$ denotes element-wise multiplication.

F. PHASE 6: HYPERPARAMETER SETTING

Table 2 presents the analysis of fine-tuning conducted. We explore the key areas of each applied model used to enhance performance by selecting critical features in deep learning models for predicting depression-related information [30]. Through iterative training and validation processes, we identify the optimal hyperparameters, which help improve efficiency and increase accuracy in depression analysis.

TABLE 2. Optimizing hyperparameters in used deep learning models.

Model	Parameters and description
LR	random_state=0, test_size=0.2, n_splits=10 ,Input Size (input_dim), random_state=Non, shuffle=True
RF	n_estimators=100, max_depth=100, random_state=0, criterion='gini', verbose=0,class_weight=None, multi_class='auto'
KN	n_neighbors=3, test_size=0.3, random_state=40,algorithm='auto', weights='uniform'
MLP	random_state=1, max_iter=35, test_size=0.2, random_state=48,nesterovs_momentum=True, power_t=0.5
LSTM	Dense(16,activation='relu'), Dense(32,activation='relu'), Dense(1,activation='sigmoid')

IV. EXPERIMENTS AND OBSERVATIONS

This section reviews the results and discusses using deep learning models for depression recognition. This study involved standard data, including different depression research cases, to test the model's effectiveness. The results and analyses of this study show that the use of deep learning models is effective in identifying the problem of depression.

A. EXPERIMENTAL SETUP

Work with deep and machine learning models, including developing complex Python programs, specifically version 3.6 of the language. The Pandas module is used to import and analyze stress data. The evaluation is carried out on Google Colab, utilizing a configuration that includes a GPU backend, 13 GB of RAM, and 90 GB of storage. To assess the performance of the machine learning models, metrics like recall, accuracy, precision, and the F1 score are employed. The used metrics are described below:

- TP = True Positives: The number of correctly identified depressed posts.
- TN = True Negatives: The number of correctly identified not depressed posts.
- FP = False Positives: The number of not-depressed posts incorrectly identified as depressed.
- FN = False Negatives: The number of depressed posts incorrectly identified as not depressed.

1) RECALL

Recall, also known as sensitivity, measures the proportion of actual depressed users that were correctly identified:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (12)$$

2) ACCURACY

Accuracy is simply a ratio of correctly predicted observations to the total observations:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

3) PRECISION

Precision, also known as positive predictive value, is the ratio of true positive predictions to the total positive predictions:

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

4) F1

The F1 score, a harmonic mean of precision and recall, ensures that the model's precision and recall are taken into account, providing a more balanced view of its performance.:

$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \quad (15)$$

B. RESULTS WITH BERT EMBEDDING FEATURES

The performance results of machine learning models applying BERT features for depression detection are analyzed in this section. The performance metrics for each method are assessed using unseen test data. Performance results from applying BERT embedding features are presented in Table 3. The analysis reveals that the Logistic Regression (LR) classifier achieved an accuracy, precision, recall, and F1 score of 0.56. The K-Neighbors classifier followed with a recall, accuracy, precision, and F1 score of 0.61. The Random Forest (RF) classifier achieved the highest performance with accuracy, precision, recall, and F1 score of 0.71. The Multi-Layer Perceptron (MLP) classifier recorded an accuracy of 0.51, a precision of 0.55, a recall of 0.51, and an F1 score of 0.42. This analysis concludes that while moderate performance scores are achieved using BERT embedding features, there is still a need for improvement.

TABLE 3. Results with BERT embedding features.

Technique	Accuracy	Precision	Recall	F1
LR	0.56	0.56	0.56	0.56
RF	0.71	0.72	0.72	0.72
KNC	0.61	0.61	0.61	0.61
MLP	0.51	0.55	0.51	0.42

TABLE 4. Class-wise performance analysis with the BERT features.

Models	Accuracy	Target Class	Precision	Recall	F1Score
LR	0.56	Depressed	0.56	0.57	0.56
		Non-Depressed	0.56	0.56	0.56
		Average	0.56	0.56	0.56
RF	0.71	Depressed	0.72	0.71	0.72
		Non-Depressed	0.72	0.73	0.72
		Average	0.72	0.72	0.72
KN	0.61	Depressed	0.60	0.63	0.62
		Non-Depressed	0.62	0.59	0.60
		Average	0.61	0.61	0.61
MLP	0.51	Depressed	0.51	0.92	0.65
		Non-Depressed	0.58	0.11	0.18
		Average	0.55	0.51	0.42

In addition, we have determined the class-wise performance results of the models applied with BERT Embedding features, as described in Table 4. The analysis reveals that the RF model achieved a 72% precision score for the depressed class. This analysis indicates that the results for each class are low.

C. RESULTS WITH NOVEL PROPOSED BERT-RF FEATURES

In this section, the performance results of the proposed BERT-RF features with deep learning models applied to depression detection are analyzed. An evaluation of the performance metrics of each method is conducted using test data. Table 5 describes the performance of the applied methods using testing data based on the BERT-RF model. Results show that the LR (Logistic Regression) classifier outperformed others with a recall of 0.99, precision of 0.99, and an F1 score of 0.99. The RF (Random Forest) classifier has an accuracy of 0.98, recall of 0.99, precision of 0.99, and an F1 score of 0.99. The K-Neighbors classifier achieves an accuracy of 0.99, precision of 0.99, recall of 0.99, and an F1 score of 0.99. The multilayer perceptron (MLP) classifier has an accuracy of 0.99, recall of 0.98, precision of 0.98, and an F1 score of 0.98. This analysis shows the superiority of the proposed BERT-RF features in achieving high-performance accuracy scores for depression recognition from social media.

TABLE 5. Results with novel proposed BERT-RF features.

Technique	Accuracy	Precision	Recall	F1
RF	0.98	0.99	0.99	0.99
KNC	0.98	0.99	0.99	0.99
MLP	0.98	0.98	0.98	0.98
LSTM	0.94	0.95	0.94	0.94
LR	**0.99**	**0.99**	**0.99**	**0.99**

Tables 6 present a class-wise performance analysis using the BERT-RF-based model. Our analysis aims to provide an overall assessment of the performance of various models on the given data, with a particular emphasis on class accuracy. The results indicate that the performance of the Multilayer Perceptron (MLP) approach achieved a score of 0.97 for the depression group, which is lower compared to others. This lower score demonstrates the challenges in accurately defining the nature of depression using the MLP approach. In contrast, other models perform well, with category scores consistently above 0.98 in our analysis. This suggests that while MLPs struggle with accurately classifying stressors, other models excel in the decision-making process across all groups in the dataset. Overall, this analysis indicates that all models achieved high-performance scores using a novel proposed approach for depression recognition from social media.

TABLE 6. Class-wise performance analysis after the BERT.

Models	Accuracy	Target Class	Precision	Recall	F1Score
RF	0.98	Depressed	0.99	0. 99	0. 99
		Non-Depressed	0. 99	0. 99	0. 99
		Average	0. 99	0. 99	0. 99
KNC	0.98	Depressed	0. 99	0. 99	0. 99
		Non-Depressed	0. 99	0. 99	0. 99
		Average	0. 99	0. 99	0. 99
MLP	0.98	Depressed	0.97	1.00	0.98
		Non-Depressed	1.00	0.97	0.98
		Average	0.98	0.98	0.98

The time series baseline chart performance results analysis of the applied LSTM model is illustrated in Figure 5. The analysis shows that the neural network LSTM achieved high error rates when the model started its training; however, after the second epoch, the results improved. In addition, we have performed the radar chart-based performance mapping, as shown in Figure 6. This analysis demonstrates the superiority of the proposed LR models for detecting depression from social media.

D. RESULTS OF PROPOSED METHOD

In this section, we examine the performance metric results of our proposed logistic regression (LR) model. Table 7 presents an overview of the performance metrics and results for a specific plan category. Our model achieves an accuracy, recall, precision, and F1 score of 0.99. This underscores the effectiveness of the LR method in accurately identifying various levels of depression, including depressed, non-depressed, and moderate cases. Performance evaluations

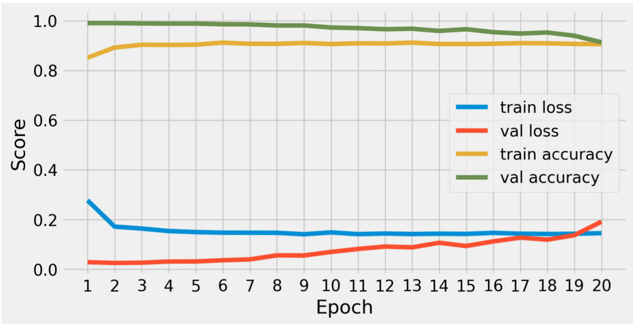


FIGURE 5. Impact of learning rate on convergence: Training loss over epoch.

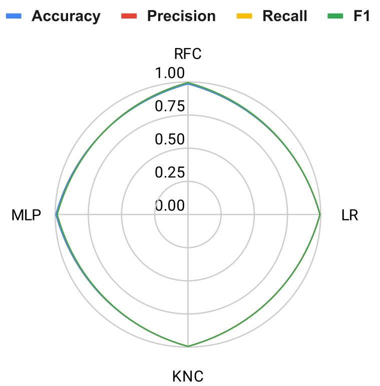


FIGURE 6. Multivariate analysis of performance metrics using radar graphs: Deep learning models.

indicate that the LR model can differentiate between these categories of depression with high accuracy and confidence.

TABLE 7. Performance results of proposed LR method.

Models	Accuracy	Target Class	Precision	Recall	F1Score
LR	0.99	Depressed	0. 99	0. 99	0. 99
		Non-Depressed	0. 99	0. 99	0. 99
		Average	0. 99	0. 99	0. 99

E. CONFUSION MATRIX RESULTS AND HISTOGRAM ANALYSIS

Figure 7 presents the outcomes of the confusion matrix analysis conducted to assess the performance of various machine learning models. The results indicate that the Multilayer Perceptron (MLP) model generated 65 incorrect predictions, the LSTM model produced 228 inaccurate predictions, and the K-Nearest Neighbors (KNN) algorithm accounted for 53 errors. In addition, the Logistic Regression (LR) model yielded 43 incorrect predictions. These findings validate the effectiveness of the error evaluation method when applied to the dataset used. Overall, the analysis suggests that the performance of these machine-learning technologies is suboptimal.

The comparison between the BERT and the proposed BERT-RF approach, as illustrated in Figures 8 and 9, demonstrates that the BERT-RF model significantly outperforms other methods. This superiority is clearly illustrated by the higher accuracy metrics using the BERT-RF model achieved on the chart. The graphical representation, particularly, underscores the superior performance of the BERT-RF approach, further supported by consistently high scores across various performance metrics.

F. KFOLD CROSS-VALIDATION RESULTS

In this section, we employ k-fold validation to assess the performance of the newly developed BERT-based logistic regression model. Table 8 illustrates that utilizing k-fold validation can enhance the prediction model's performance by mitigating the effects of variance across different datasets and facilitating a more accurate evaluation of the model's predictive capability. We opted for a 10-fold validation approach to analyze the results. The aggregated model demonstrated a remarkable average k-fold accuracy of 0.99. Ultimately, the analysis revealed that the composites prepared using logistic regression (LR) achieved a significance level of 0.99 and a minimal variance of (+/−) 0.0131. These findings underscore the reliability and consistency of the proposed BERT-RF-based logistic regression model in delivering accurate and stable outcomes.

TABLE 8. The 10-fold-based performance validations Bert base LR model.

K-Folds	Kfold Accuracy
1	0.98
2	0.99
3	0.99
4	0.98
5	0.98
6	0.98
7	0.98
8	0.98
9	0.94
10	0.99
Average	**0.99**
Standard Deviation (+/-)	**0.0131**

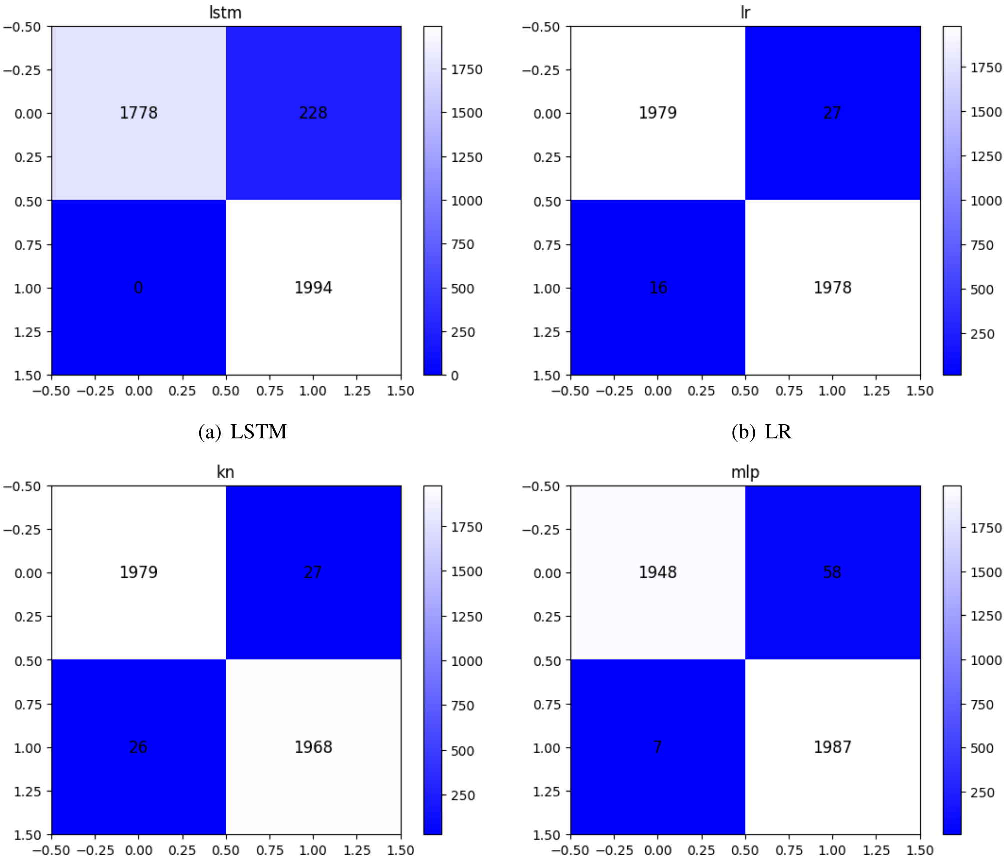
In addition, we also performed a k-fold cross-validation analysis of other applied methods, as shown in Table 9. This analysis further demonstrates that by utilizing the proposed BERT-RF features, all applied machine learning models achieved generalization in detecting depression from social media.

TABLE 9. Kfold results of all applied methods.

Method	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean Accuracy
RF	0.983	0.984	0.985	0.985	0.985	0.98
MLP	0.990	0.989	0.988	0.990	0.988	0.99
KNC	0.988	0.987	0.98	0.99	0.987	0.99

G. STATISTICAL T-TEST ANALYSIS

We have also conducted a statistical T-Test analysis to compare the proposed Logistic Regression (LR) approach against other methodologies, as illustrated in Table 10. This analysis reveals that our proposed approach significantly



(a) LSTM (b) LR

(c) KNC (d) MLP

FIGURE 7. **The performance evaluation: Confusion matrix analysis.**

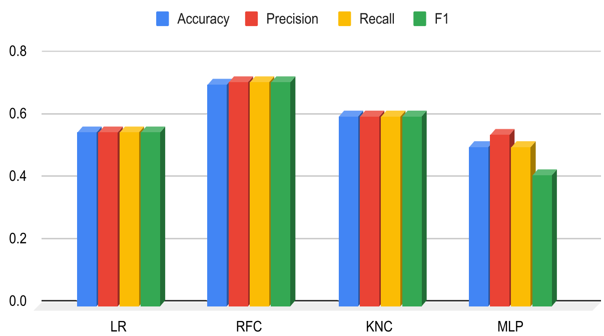


FIGURE 8. **Histogram results with only BERT features.**

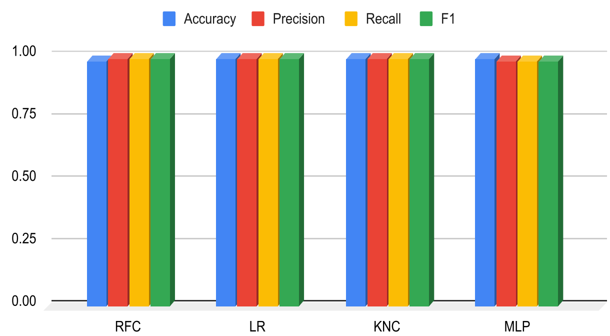


FIGURE 9. **Histogram results with proposed BERT-RF features.**

outperforms the alternatives in terms of performance scores, leading to the rejection of the null hypothesis in each instance for the detection of depression.

H. FEATURE SPACE ANALYSIS WITH PROPOSED BERT-RF

We also visualized the features using a 3D scatter plot, which is a visualization technique. This analysis aims to explore and represent data in three-dimensional space, as shown in Figure 10. Data points are viewed line by line in 3D space, where closeness in the diagram indicates the similarity of the main points. This analysis shows that newly created features using the BERT-RF approach are highly linearly separable, which helps us achieve high-performance results for applied machine learning models.

TABLE 10. Results of statistical T-Test analysis.

Proposed vs. Others	T-statistic	P-value	Null Hypothesis (H_o)
LR vs RF	108.99	1.702	Rejected
LR vs MLP	inf	0.0	Rejected
LR vs KN	17.90	0.0003	Rejected
LR vs LSTM	19.0	0.0003	Rejected

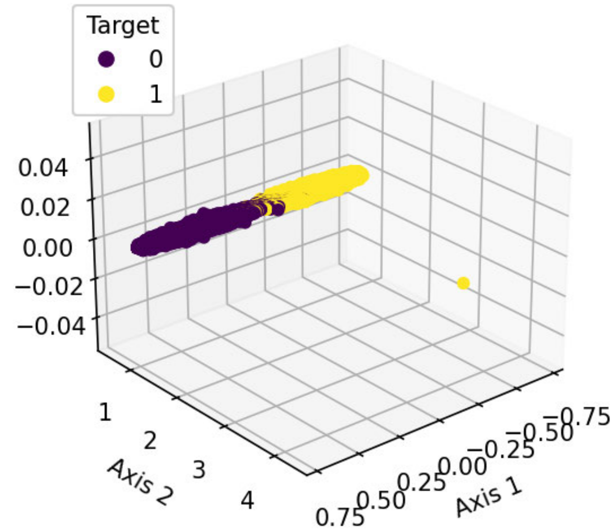


FIGURE 10. Feature reduction for improved insight: PCA in text.

TABLE 11. State of the art results comparisons of the proposed approach.

Ref.	Proposed Approach	Performance Score
[31]	DistilBert	89%
[13]	Random forest algorithm	77%
[16]	logistic regression classifier	86%
[14]	TF-IDF Apporach	89%
[32]	Convolutional Neural Network(CNN)	94%
Our	**BERT-RF Logistic Regression**	**99%**

I. STATE OF THE ART RESULTS COMPARISON

This section focuses on objective and qualitative analysis in state-of-the-art comparison analyses. The basis of our research is to compare our scheme with previous studies examining depression data, as shown in Table 11. The comparison results show that our proposed LR method stands out in the search for depression detection. What sets it apart is its exceptional quality, which boasts an impressive accuracy of 0.99. It plays a crucial role in bridging the gap observed in previous studies. Our scheme successfully addresses the discrepancy between the best-performing scores in the search for depression. By achieving high accuracy, our method not only proves its effectiveness in the study but also contributes to the advancement of depression research and the treatment of limitations identified in previous studies.

J. DISCUSSIONS AND LIMITATIONS

Our research on detecting depression from social data using BERT-based content embeddings and advanced probabilistic features provides a new way to understand negative emotions. Although our method significantly improves to 0.99% accuracy, some inconsistent studies and limitations are worth noting.

- First, the generalizability of our model across many social networks, demographic groups, and cultural contexts remains an area for investigation. Examining different regulations and their long-term performance will increase the validity of our approach.
- Additionally, considering the use of BERT-based embeddings, the interpretation of the prediction model needs to be further evaluated for clarity and reliability.
- Ethical considerations regarding mental health profiling and responsible use of information on social media should be validated, including issues of user consent and privacy.
- Additionally, our model is based on specific language patterns that express melancholy. This leads to a discussion of the possible limitations of why individuals may display melancholic behaviour differently in less formal settings.

V. CONCLUSION AND FUTURE DIRECTIONS

This article presents advanced machine learning models for stress analysis, including Random Forest Classifier (RFC), Multilayer Perceptron (MLP), K-Nearest Neighbors Classifier (KNC), and Logistic Regression (LR), with a focus on BERT-based deep learning techniques. The results demonstrate that the proposed scheme is highly effective, achieving an accuracy rate of 99%, and outperforms existing models in detecting depression. This study aims to contribute to the field by addressing the limitations of previous research and showcasing the effectiveness of deep learning in identifying patterns of depression. These findings are significant and promising for both the research and treatment of depression. The success and accuracy of this study underscore the potential of novel machine-learning approaches in mental health. Overall, this study underscores the critical role of deep learning models in accurately identifying and understanding depression, offering insights into future developments in this field.

A. FUTURE WORK

In future work, we will build a web-based API framework that detects depression from user posts in real-time on social media platforms.

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REFERENCES

[1] D. William and D. Suhartono, "Text-based depression detection on social media posts: A systematic literature review," *Proc. Comput. Sci.*, vol. 179, pp. 582–589, Jan. 2021.

[2] J. S. L. Figuerêdo, A. L. L. M. Maia, and R. T. Calumby, "Early depression detection in social media based on deep learning and underlying emotions," *Online Social Netw. Media*, vol. 31, Sep. 2022, Art. no. 100225.

[3] H. Zogan, I. Razzak, S. Jameel, and G. Xu, "DepressionNet: A novel summarization boosted deep framework for depression detection on social media," 2021, *arXiv:2105.10878*.

[4] S. S and J. S. Raj, "Analysis of deep learning techniques for early detection of depression on social media Network–A comparative study," *J. Trends Comput. Sci. Smart Technol.*, vol. 3, no. 1, pp. 24–39, May 2021.

[5] J. D. J. Titla-Tlatelpa, R. M. Ortega-Mendoza, M. Montes-y-Gómez, and L. Villaseñor-Pineda, "A profile-based sentiment-aware approach for depression detection in social media," *EPJ Data Sci.*, vol. 10, no. 1, p. 54, Dec. 2021.

[6] V. Adarsh, P. A. Kumar, V. Lavanya, and G. R. Gangadharan, "Fair and explainable depression detection in social media," *Inf. Process. Manage.*, vol. 60, no. 1, Jan. 2023, Art. no. 103168.

[7] E. A. Ríssola, S. A. Bahrainian, and F. Crestani, "A dataset for research on depression in social media," in *Proc. 28th ACM Conf. User Modeling, Adaptation Personalization*, Jul. 2020, pp. 338–342.

[8] H. Senra and S. McPherson, "Depression in disabling medical conditions—Current perspectives," *Int. Rev. Psychiatry*, vol. 33, no. 3, pp. 312–325, Apr. 2021.

[9] S. C. Guntuku, D. B. Yaden, M. L. Kern, L. H. Ungar, and J. C. Eichstaedt, "Detecting depression and mental illness on social media: An integrative review," *Current Opinion Behav. Sci.*, vol. 18, pp. 43–49, Dec. 2017.

[10] S. Almouzini, M. Khemakhem, and A. Alageel, "Detecting Arabic depressed users from Twitter data," *Proc. Comput. Sci.*, vol. 163, pp. 257–265, Jan. 2019.

[11] J. Deepali, J. Makhija, Y. Nabar, and N. Nehet, "Mental health analysis using deep learning for feature extraction," Tech. Rep., 2018.

[12] T. Gui, "Cooperative multimodal approach to depression detection in Twitter," in *Proc. AAAI Conf. Artif. Intell.*, vol. 33, no. 1, Jul. 2019, pp. 110–117.

[13] F. Azam, M. Agro, M. Sami, M. H. Abro, and A. Dewani, "Identifying depression among Twitter users using sentiment analysis," in *Proc. Int. Conf. Artif. Intell. (ICAI)*, Apr. 2021, pp. 44–49.

[14] P. Kumar, P. Samanta, S. Dutta, M. Chatterjee, and D. Sarkar, "Feature based depression detection from Twitter data using machine learning techniques," *J. Sci. Res.*, vol. 66, no. 2, pp. 220–228, 2022.

[15] S. Pachouly, G. Raut, K. Bute, R. Tambe, and S. Bhavsar, "Depression detection on social media network (Twitter) using sentiment analysis," *Int. Res. J. Eng. Technol.*, vol. 8, pp. 1834–1839, Jan. 2021.

[16] S. Jain, S. P. Narayan, R. K. Dewang, U. Bhartiya, N. Meena, and V. Kumar, "A machine learning based depression analysis and suicidal ideation detection system using questionnaires and Twitter," in *Proc. IEEE Students Conf. Eng. Syst. (SCES)*, May 2019, pp. 1–6.

[17] H. Kour and M. K. Gupta, "An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM," *Multimedia Tools Appl.*, vol. 81, no. 17, pp. 23649–23685, Jul. 2022.

[18] R. Safa, P. Bayat, and L. Moghtader, "Automatic detection of depression symptoms in Twitter using multimodal analysis," *J. Supercomput.*, vol. 78, no. 4, pp. 4709–4744, Mar. 2022.

[19] D. B. Victor, J. Kawsher, M. S. Labib, and S. Latif, "Machine learning techniques for depression analysis on social media-case study on Bengali community," in *Proc. 4th Int. Conf. Electron., Commun. Aerosp. Technol. (ICECA)*, Nov. 2020, pp. 1118–1126.

[20] S. R. Kamite and V. B. Kamble, "Detection of depression in social media via Twitter using machine learning approach," in *Proc. Int. Conf. Smart Innov. Design, Environ., Manage., Planning Comput. (ICSIDEMPC)*, Oct. 2020, pp. 122–125.

[21] INFAMOUSCODER. *Depression: Twitter Dataset + Feature Extraction*. Accessed: Nov. 2, 2024. [Online]. Available: https://www.kaggle.com/datasets/infamouscoder/mental-health-social-media

[22] M. I. Mobin, M. F. Mridha, and S. H. Mahmud, "Exploratory analysis of suicidal tendency in depression investigation social media post," Tech. Rep., 2024.

[23] A. Raza, K. Munir, and M. Almutairi, "A novel deep learning approach for deepfake image detection," *Appl. Sci.*, vol. 12, no. 19, p. 9820, Sep. 2022.

[24] A. Raza, I. Akhtar, L. Abualigah, R. A. Zitar, M. Sharaf, M. S. Daoud, and H. Jia, "Preventing road accidents through early detection of driver behavior using smartphone motion sensor data: An ensemble feature engineering approach," *IEEE Access*, vol. 11, pp. 138457–138471, 2023.

[25] A. Raza, A. M. Qadri, I. Akhtar, N. A. Samee, and M. Alabdulhafith, "LogRF: An approach to human pose estimation using skeleton landmarks for physiotherapy fitness exercise correction," *IEEE Access*, vol. 11, pp. 107930–107939, 2023.

[26] A. Raza, F. Rustam, H. U. R. Siddiqui, I. D. L. T. Diez, B. Garcia-Zapirain, E. Lee, and I. Ashraf, "Predicting genetic disorder and types of disorder using chain classifier approach," *Genes*, vol. 14, no. 1, p. 71, Dec. 2022.

[27] A. Raza, K. Munir, M. S. Almutairi, and R. Sehar, "Novel class probability features for optimizing network attack detection with machine learning," *IEEE Access*, vol. 11, pp. 98685–98694, 2023.

[28] A. Raza, F. Rustam, H. U. R. Siddiqui, I. D. L. T. Diez, and I. Ashraf, "Predicting microbe organisms using data of living micro forms of life and hybrid microbes classifier," *PLoS ONE*, vol. 18, no. 4, Apr. 2023, Art. no. e0284522.

[29] A. Raza, K. Munir, M. S. Almutairi, and R. Sehar, "Novel transfer learning based deep features for diagnosis of down syndrome in children using facial images," *IEEE Access*, vol. 12, pp. 16386–16396, 2024.

[30] A. Alsaeedi and M. Z. Khan, "A study on sentiment analysis techniques of Twitter data," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 2, pp. 361–374, 2019.

[31] M. Rizwan, M. F. Mushtaq, U. Akram, A. Mehmood, I. Ashraf, and B. Sahelices, "Depression classification from tweets using small deep transfer learning language models," *IEEE Access*, vol. 10, pp. 129176–129189, 2022.

[32] A. A. Baale, O. R. Olasunkanmi, F. E. Adelodun, and A. A. Adigun, "Opinion analysis and machine learning modeling for depression detection," Tech. Rep.

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