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Mental Health Safety and Depression Detection in Social Media Text Data: A Classification Approach Based on a Deep Learning Model

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Abstract: Social media platforms serve as a rich source of data for monitoring mental health, providing timely insights for early detection of depression through automated analysis of user-generated content. Utilizing the Mental Health Social Media dataset from Kaggle, this study investigates the effectiveness of deep learning models in classifying depression-related text. The data undergo comprehensive preprocessing, including normalization, HTML and URL removal, tokenization, and label encoding, followed by embedding and vectorization techniques such as BERT embeddings, Keras Tokenizer, and TF-IDF vectorization to capture semantic and contextual information. Data balancing methods, including SMOTE and random oversampling, are applied to address class imbalance. Multiple architectures, including BERT-based LSTM, BERT-BiLSTM, BERT-LSTM-GRU hybrids, standalone LSTM and GRU networks, and traditional machine learning classifiers such as Random Forest, SVM, and Voting Classifier are evaluated. Experimental results demonstrate that the Voting Classifier achieves the highest performance with an accuracy of 93.9%, F1-score of 93.7%, and ROC-AUC of 87.5%, outperforming individual deep learning and classical models. The analysis confirms that combining multiple models through ensemble learning significantly enhances the detection capability, providing a robust framework for accurate and context-aware depression classification from social media text, which can support timely mental health interventions and monitoring at scale.
Keywords: Depression Detection, Social Media Analysis, Deep Learning, BERT Embeddings, LSTM, GRU, Random Forest, Explainable AI.

I. INTRODUCTION

Mental health safety emphasizes proactive measures to prevent, detect, and manage psychological conditions, ensuring the well-being of individuals across healthcare and societal contexts. Among mental health disorders, depression is one of the most prevalent, characterized by persistent sadness, loss of interest, and emotional distress. According to forecasts from the World Health Organization, unipolar depressive disorder is projected to become the leading cause of disease burden in high-income nations by 2030 [6]. In contemporary digital environments, social media has become a significant factor influencing mental health dynamics. While platforms offer opportunities for social interaction and emotional expression, they also expose users to stressors such as social comparison, cyberbullying, and information overload, potentially exacerbating depressive tendencies [3], [4].

As individuals increasingly share thoughts and emotions online, social media text provides a rich, real-time source of behavioral data reflecting mental states [2]. Advances in artificial intelligence, particularly natural language processing (NLP), have enabled systems capable of analyzing language patterns associated with mental health conditions [1], [5]. Techniques integrating deep learning architectures, including LSTM, BiLSTM, and CNN, alongside word embeddings like BERT and TF-IDF, have shown promise in capturing semantic relationships and contextual dependencies essential for accurate detection of depressive expressions [10]. Machine learning approaches such as Random Forest and SVM complement deep learning models by providing alternative classification perspectives, enhancing robustness and prediction reliability [2], [4].

The purpose of this work is to develop an automated framework capable of accurately detecting depression from social media text while maintaining interpretability and adaptability. By leveraging comprehensive preprocessing, multiple embeddings, deep learning and classical machine learning models, and explainable AI techniques, the system aims to support early identification of depressive tendencies, provide actionable insights, and facilitate timely interventions, thereby contributing to improved mental health monitoring and support in digital communication environments [7], [8], [9]

II. RELATED WORK

Recent advancements in artificial intelligence have significantly impacted mental health assessment, particularly in detecting depression through analysis of textual data from social media platforms. Traditional methods for depression screening, such as self-reported questionnaires and clinical interviews, although effective, are often time-consuming, subjective, and limited in scalability. Consequently, researchers have turned to computational approaches to develop automated systems capable of analyzing large volumes of social media text to identify linguistic and emotional indicators associated with depression [11].

Several studies have explored deep learning frameworks for depression detection, demonstrating their effectiveness in capturing complex semantic and syntactic patterns in user-generated content. Amanat et al. [12] proposed a deep learning-based model for identifying depressive expressions in text, emphasizing the utility of neural networks in understanding contextual relationships between words. Similarly, Xin and Zakaria [13] integrated BERT embeddings with convolutional neural networks (CNN) and bidirectional LSTM networks to develop an explainable framework for depression detection, demonstrating that combining contextualized embeddings with sequential modeling improves prediction accuracy and interpretability. Transformer-based architectures have also been employed for this task, leveraging self-attention mechanisms to capture long-range dependencies in text sequences, enabling robust modeling of subtle emotional cues and temporal patterns [14].

Structured approaches using LSTM networks have gained traction due to their ability to model sequential dependencies in text. Uddin [15] applied long short-term memory networks with neural structured learning for depression detection, highlighting the importance of learning temporal relationships within textual data. Kamalam et al. [16] explored text-based diagnostic frameworks using social media posts, illustrating those preprocessing techniques such as tokenization, stop-word removal, and embedding representations are critical in enhancing model performance and ensuring the reliability of predictions. Mao et al. [17] proposed combining bidirectional LSTM networks with time-distributed CNN layers to predict depression severity, emphasizing the role of both semantic features and prosodic cues in understanding emotional states. These hybrid architectures show improved capability in capturing subtle variations in text indicative of depressive tendencies.

Research has also focused on the integration of linguistic metadata with neural networks to improve early detection of depression. Trotzek et al. [18] incorporated linguistic features such as part-of-speech tags, syntactic structures, and lexical indicators alongside deep learning models, demonstrating enhanced accuracy in identifying early signs of depression from textual sequences. This approach underscores the importance of combining content-based and metadata-driven features to improve system reliability and sensitivity, particularly in heterogeneous social media datasets. BERT-based methodologies have gained particular attention due to their contextual understanding of language. Raj et al. [19] utilized BERT embeddings for social media depression detection, illustrating that contextual word representations can capture nuanced emotional expressions and improve classification performance compared to traditional word embeddings.

Moreover, Hasan and Ghane [20] implemented a data-driven depression detection system on Twitter, leveraging deep learning models to analyze user-generated posts. Their work highlighted the effectiveness of combining pre-trained embeddings with supervised learning approaches to classify depressive versus non-depressive content accurately. Across these studies, common challenges include handling informal language, slang, abbreviations, and emojis prevalent in social media posts, which can obscure semantic meaning and hinder model performance. Preprocessing strategies such as normalization, emoji translation, and contextual embedding generation have been shown to mitigate these issues, enhancing model interpretability and robustness.

III. METHODOLOGY

The system presents an automated framework for detecting depression in social media text by leveraging both deep learning and classical machine learning techniques [21], [25]. Raw text from the Mental Health Social Media dataset undergoes preprocessing including normalization, removal of HTML tags, URLs, non-printable characters, tokenization, and label encoding to create structured inputs suitable for modeling. Embedding and vectorization methods such as BERT embeddings, TF-IDF vectorization, and Keras Tokenizer are employed to capture semantic and contextual information. The framework explores multiple deep learning architectures including LSTM, GRU, BERT-LSTM, and BERT-BiLSTM, alongside classical models like Random Forest and SVM to enhance classification capabilities. As an extension, SMOTE is applied for dataset balancing, and advanced ensembles including LSTM + GRU, BERT embeddings LSTM + GRU, and a Voting Classifier are incorporated. Explainable AI techniques, LIME and SHAP, provide transparent insights into feature importance, while a Flask-based interface enables real-time user input, prediction, and topic modeling [23], [26].

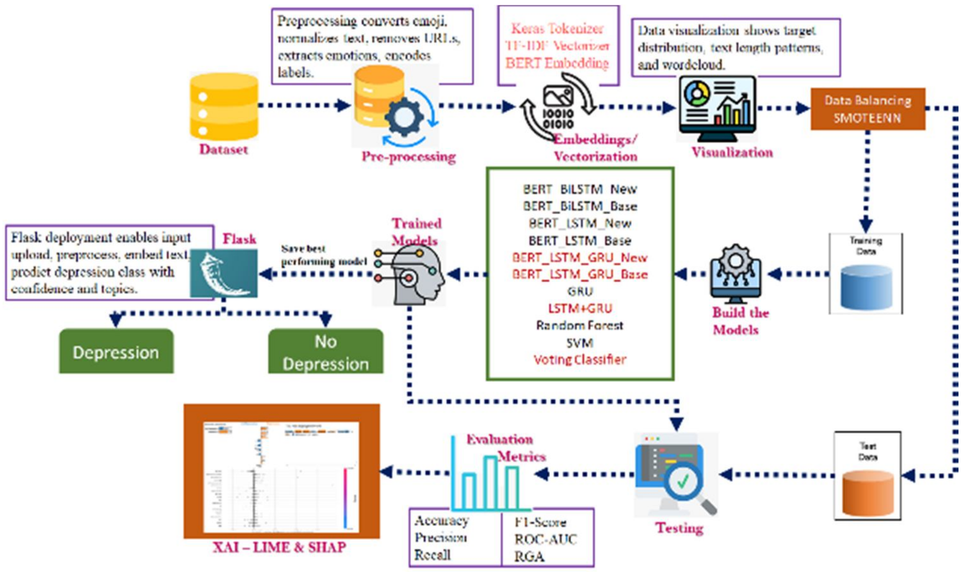

Fig.1 Proposed Architecture

Figure 1 shows the workflow for developing and evaluating various natural language processing models. The process begins with "Dataset Collection" and subsequent "Data Preprocessing." This prepared data is then used in the "Models Construction" phase. This stage involves building several models: a BERT-BiLSTM with new modules, a baseline BERT-BiLSTM, a BERT-LSTM with new modules, and a baseline BERT-LSTM. After construction, these models undergo "Model Training". Finally, the trained models are subjected to "Model Evaluation and Comparative Analysis," where their performance is assessed and compared to determine the most effective architecture. This systematic approach ensures a thorough comparison of different model configurations.

A. Dataset Collection

The dataset used for depression detection was collected from Twitter, consisting of 20,000 posts, each labeled as either "Depression" or "No Depression." [22] Each entry contains metadata including post ID, creation timestamp, user ID, followers, friends, favorites, statuses, retweets, and the textual content of the post. After removing unnecessary columns, the dataset contains ten relevant attributes with no missing values, ensuring data completeness and consistency. The labels are balanced, with 10,000 posts corresponding to each class, which provides a uniform distribution for model training and evaluation. Figure 2 illustrates the distribution of depression labels, highlighting the equal representation of depressive and non-depressive posts. The dataset serves as a reliable foundation for text-based analysis, enabling the development of robust machine learning and deep learning models for early detection of depression in social media text.

	Unnamed: 0	post_id	post_created	post_text	user_id	followers	friends	favourites	statuses	retweets	label
0	0	637894677824413696	Sun Aug 30 07:48:37 +0000 2015	It's just over 2 years since I was diagnosed w...	1013187241	84	211	251	837	0	1
1	1	637890384576778240	Sun Aug 30 07:31:33 +0000 2015	It's Sunday, I need a break, so I'm planning t...	1013187241	84	211	251	837	1	1
2	2	637749345908051968	Sat Aug 29 22:11:07 +0000 2015	Awake but tired. I need to sleep but my brain ...	1013187241	84	211	251	837	0	1
3	3	637696421077123073	Sat Aug 29 18:40:49 +0000 2015	RT @SewHQ: #Retro bears make perfect gifts and...	1013187241	84	211	251	837	2	1
4	4	637696327485366272	Sat Aug 29 18:40:26 +0000 2015	It's hard to say whether packing lists are mak...	1013187241	84	211	251	837	1	1

Fig.2 Dataset Collection

B. *Pre-processing*

Preprocessing involves cleaning and structuring raw social media text to enhance model performance. Steps include converting text to lowercase, removing HTML tags, URLs, and non-printable characters, selectively handling punctuation based on model requirements, tokenizing words into meaningful units, and applying label encoding to convert categorical labels into numeric form suitable for machine learning algorithms.

1) *Data Processing:* Data processing transforms raw textual data into structured formats for effective analysis. Initially, posts are filtered for noise and irrelevant content, followed by tokenization to split sentences into words or subwords. Features such as post length, frequency of special characters, and user metadata are extracted to enrich textual representation. Label encoding converts depression classes into numeric labels. Combined with proper normalization and cleaning, these steps ensure consistency, reduce data sparsity, and prepare high-quality inputs for training both classical machine learning models and advanced deep learning architectures.
2) *Embeddings/Vectorization:* Embeddings and vectorization convert textual data into numerical representations that capture semantic and contextual information. Keras Tokenizer encodes text sequences into integer tokens suitable for neural networks. TF-IDF vectorization measures word importance relative to the dataset, providing sparse feature vectors for classical models. BERT embeddings generate contextualized dense vectors, capturing both syntax and meaning within sentences. By leveraging these methods, models can understand nuanced language patterns, emotional cues, and temporal dependencies in social media posts, improving predictive accuracy for depression detection. The combination of traditional and deep embeddings ensures flexibility for diverse modeling approaches.
3) *Data Visualization:* Data visualization provides insights into the dataset's structure and label distribution. Count plots show the number of depressives versus non-depressive posts, highlighting dataset balance. Word clouds reveal the most frequently used terms within each class, offering qualitative understanding of linguistic patterns associated with depression. Additional visualizations, such as histograms of post lengths or user engagement metrics, help identify trends and anomalies in the data. These visual insights support informed decisions regarding preprocessing, feature selection, and model design, ultimately improving the interpretability and robustness of depression detection models.
4) *Data Balancing:* Data balancing addresses class imbalance and ensures equitable model training. Techniques like SMOTE generate synthetic samples for the minority class, while random oversampling duplicates existing instances to equalize label distribution. Balanced datasets prevent models from biasing toward dominant classes and improve generalization to unseen data. Proper balancing enhances predictive performance, reduces false negatives, and ensures that both depressive and non-depressive posts are equally represented during training. These methods are critical for robust classification, particularly when handling real-world social media data with varying prevalence of depression-related posts.

C. *Train & Test*

The dataset is split into training and testing subsets to ensure reliable model evaluation and generalization. An 80:20 ratio is applied, where 80 percent of the data is used for training the models and 20 percent is reserved for testing their predictions on unseen samples. The training set provides sufficient examples for the models to learn patterns, linguistic cues, and contextual relationships within social media text. The testing set, kept separate, is used to validate the models' ability to correctly classify new posts as depressive or non-depressive. This division helps prevent overfitting, ensures unbiased assessment, and allows for fine-tuning of model parameters. The structured split also facilitates reproducibility and consistent comparison between different modeling approaches, ensuring that learned representations generalize well across the entire dataset.

D. *Algorithms*

1) BERT-BiLSTM: BERT-BiLSTM combines BERT embeddings with a bidirectional LSTM network to leverage both contextual word representations and sequential dependencies in text. BERT captures deep semantic meaning by considering word context from both directions, while [24] BiLSTM processes sequences forward and backward, enabling the model to understand the flow of information within sentences. This combination is particularly effective for sentiment or depression detection in social media text, where context and word order influence meaning. The purpose is to enhance classification accuracy by integrating powerful contextual embeddings with temporal dependencies, allowing the system to identify subtle linguistic cues indicative of depressive behavior in user-generated content.

2) BERT-LSTM: BERT-LSTM merges BERT embeddings with a unidirectional LSTM network to extract semantic and sequential features from text. BERT provides rich, context-aware word embeddings, while LSTM captures temporal dependencies, learning patterns in the order of words. [28] This architecture is used for tasks like depression detection, where understanding both meaning and sequence is essential. The purpose is to achieve accurate classification by combining semantic understanding with sequential learning, enabling detection of nuanced emotional expressions in social media text. By integrating these models, the system can effectively distinguish depressive content from neutral or positive text with improved performance.
3) BERT-LSTM-GRU: BERT-LSTM-GRU integrates BERT embeddings with both LSTM and GRU layers to leverage contextual, sequential, and gated recurrent capabilities. BERT captures deep semantic meaning, LSTM extracts long-term dependencies, and GRU efficiently handles sequence patterns with fewer parameters. This combination is used in social media depression detection to model complex textual structures and subtle emotional expressions. [27] The purpose is to maximize predictive accuracy and capture nuanced linguistic cues by combining the strengths of all three components, providing robust context-aware classification while reducing computational complexity compared to deeper recurrent networks.
4) LSTM: LSTM, or Long Short-Term Memory, is a type of recurrent neural network designed to capture long-term dependencies in sequential data. It uses gates to control the flow of information, allowing the network to retain or forget information over time. In the depression detection system, [29] LSTM is applied to process text sequences, understanding patterns and dependencies between words that indicate depressive sentiment. The purpose is to model temporal relationships effectively, providing accurate predictions even when relevant cues are distributed across long sentences or multiple text segments, enhancing the detection of emotional or contextual patterns.

The equation below represents the hidden state update in LSTM.

$$h_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \cdot \tanh(C_t) \qquad (1)$$

a) GRU: GRU, or Gated Recurrent Unit, is a simplified variant of LSTM that captures sequential dependencies with fewer parameters. It combines the forget and input gates into a single update gate, making it computationally efficient while retaining the ability to model long-term dependencies. In social media depression detection, GRU processes sequences of text to identify patterns indicative of emotional distress. The purpose is to learn temporal relationships in user-generated content effectively, enabling the detection of subtle signs of depression while reducing training time and resource requirements compared to traditional LSTM networks.

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \qquad (2)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \qquad (3)$$

b) Random Forest: Random Forest is an ensemble machine learning algorithm that constructs multiple decision trees and aggregates their predictions to improve accuracy and reduce overfitting. Each tree is trained on a random subset of features and samples, ensuring diversity among learners. In depression detection, Random Forest is used to classify text features derived from embeddings or vectorized representations. The purpose is to provide robust and interpretable predictions, leveraging the combined wisdom of multiple trees to handle complex patterns in text data and achieve reliable classification of depressive versus non-depressive content.

The Gini Equation given below:

$$Gini = 1 - \sum_{i=1}^{C} (Pi)^2 \qquad (4)$$

c) SVM: Support Vector Machine (SVM) is a supervised machine learning algorithm that separates data points using an optimal hyperplane, maximizing the margin between classes. It is effective for high-dimensional and sparse data, such as text embeddings. In social media depression detection, [30] SVM is applied to classify vectorized features derived from text preprocessing and embeddings. The purpose is to achieve accurate binary or multi-class classification by finding the decision boundary that best separates depressive content from non-depressive content. SVM provides robustness against overfitting, especially when the feature space is large relative to the number of training samples.

The Objective Function for Soft Margin SVM equation given below:

$$minimize\ \frac{1}{2}||W||^2 + C\sum_{i=1}^{n} \xi_i \qquad (5)$$

d) Voting Classifier: Voting Classifier is an ensemble learning method that combines predictions from multiple models to produce a final output based on majority voting or weighted probabilities. It integrates both deep learning models like BERT-LSTM and classical models like Random Forest or SVM. In depression detection, it aggregates the strengths of different classifiers to improve overall accuracy and robustness. The purpose is to reduce individual model bias, enhance predictive performance, and provide more reliable classification outcomes. By leveraging complementary strengths of diverse models, the Voting Classifier delivers context-aware and accurate detection of depressive sentiment in social media text.

The equation below represents the majority voting process in classifiers.

$$\hat{y} = argmax_c\left(\sum_{i=1}^{n} II\ (\hat{y}_i = c)\right) \qquad (6)$$

IV. EXPERIMENTAL RESULTS

1) Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \qquad (7)$$

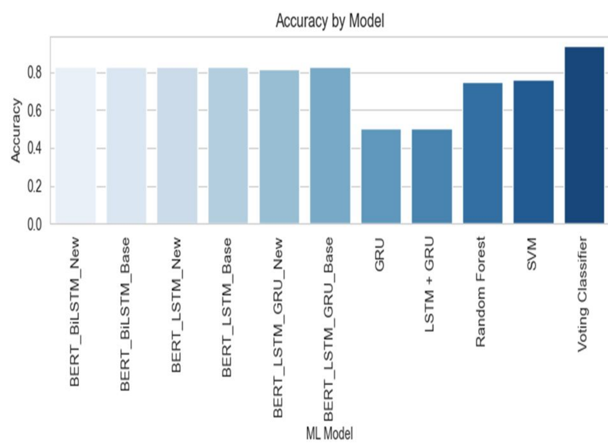

Fig.3 Accuracy

2) Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \qquad (8)$$

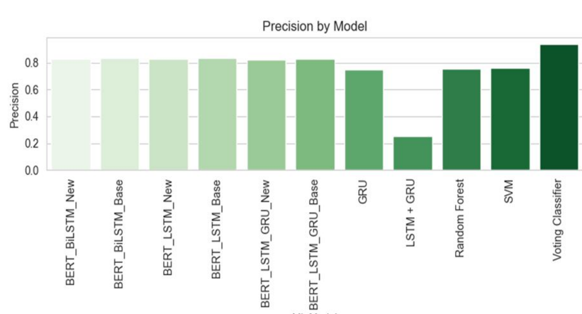

Fig.4Precision

3) Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (9)$$

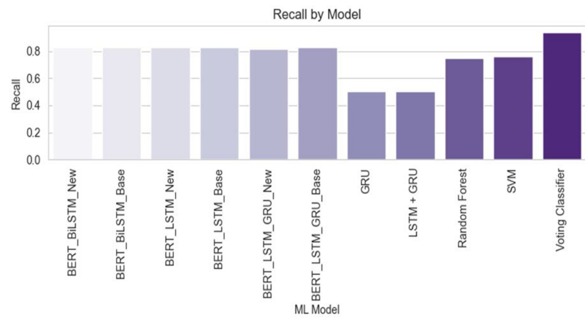

Fig.5 Recall

4) F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\,Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 \qquad (10)$$

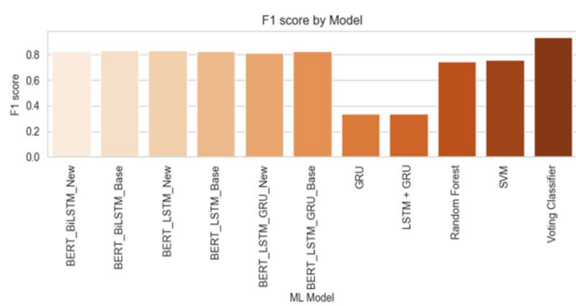

Fig.6 F1-Score

5) AUC-ROC Curve: The AUC-ROC Curve is a performance measurement for classification problems at various threshold settings. ROC plots the True Positive Rate against the False Positive Rate. AUC quantifies the overall ability of the model to distinguish between classes, where a higher AUC indicates better model performance.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \qquad (11)$$

ML Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC	RGA
BERT-BiLSTM-New	0.828	0.828	0.828	0.827	0.917	0.655
BERT-BiLSTM-Base	0.831	0.831	0.831	0.831	0.918	0.662
BERT-LSTM-New	0.830	0.830	0.830	0.830	0.918	0.660
BERT-LSTM-Base	0.828	0.831	0.828	0.828	0.917	0.657
BERT-LSTM-GRU-New	0.814	0.819	0.815	0.814	0.913	0.629
BERT-LSTM-GRU-Base	0.826	0.826	0.826	0.826	0.917	0.652

GRU	0.505	0.750	0.505	0.339	0.514	0.010
LSTM + GRU	0.505	0.255	0.505	0.339	0.507	0.010
Random Forest	0.750	0.754	0.750	0.748	0.839	0.513
SVM	0.762	0.762	0.762	0.762	0.848	0.539
Voting Classifier	0.939	0.938	0.939	0.937	0.875	0.896

Table.1 Performance Evaluation

Table 1 presents the performance comparison of various models for depression detection, including deep learning and classical approaches, highlighting metrics such as accuracy, precision, recall, F1 score, ROC-AUC, and RGA.

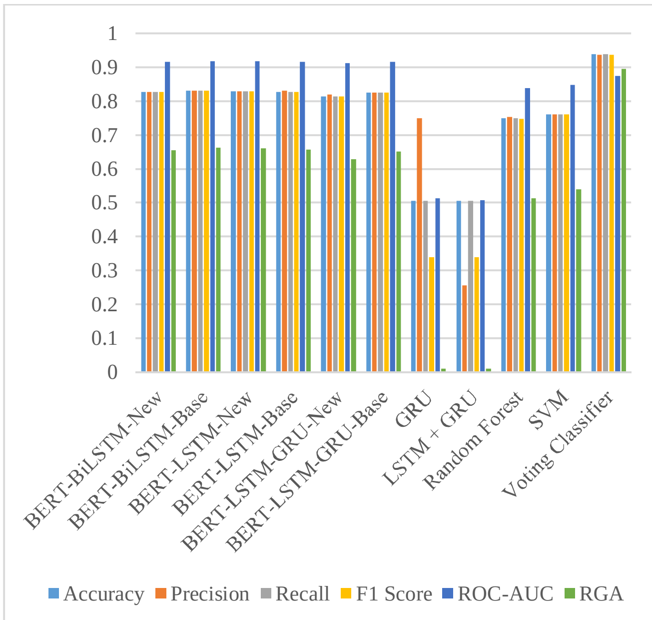

Fig.7. Comparison Graph

Figure 6 displays a comparative performance analysis of various models on different metrics: Accuracy, Precision, Recall, F1 Score, ROC-AUC, and RGA. The "Voting Classifier" consistently demonstrates the highest scores across most metrics.

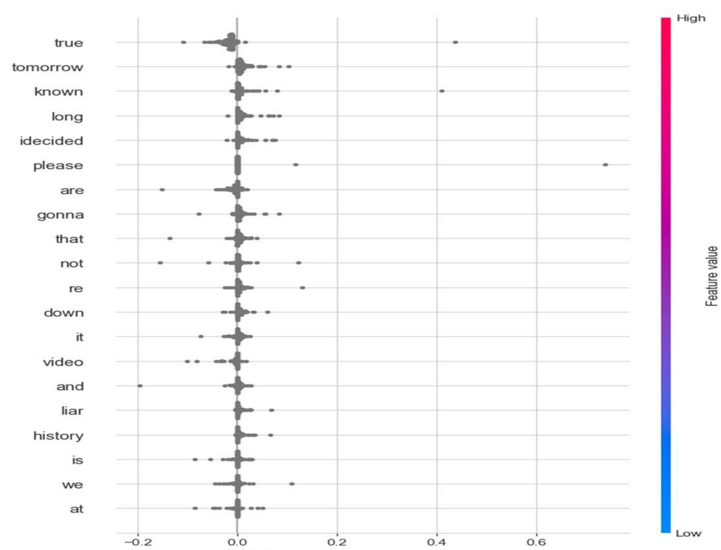

Fig.8. SHAP values showing their impact

V. CONCLUSION AND FUTURE WORK

Social media text data provides a valuable resource for monitoring mental health conditions, particularly depression, by enabling timely and automated analysis of user-generated content. The study demonstrates that deep learning architectures, combined with effective preprocessing, embedding, and data balancing techniques, can significantly enhance classification accuracy. Techniques such as BERT embeddings, TF-IDF vectorization, and Keras Tokenizer enabled the models to capture contextual and semantic nuances in text, while SMOTE and random oversampling addressed class imbalance effectively. Various models, including BERT-LSTM, BERT-BiLSTM, BERT-LSTM-GRU, standalone LSTM and GRU networks, as well as classical classifiers such as Random Forest and SVM, were evaluated to determine their effectiveness. Among all evaluated methods, the Voting Classifier exhibited superior performance, achieving an accuracy of 93.9%, F1-score of 93.7%, and ROC-AUC of 87.5%, highlighting the advantages of ensemble learning in leveraging complementary strengths of multiple algorithms. The results indicate that integrating deep learning with ensemble techniques provides a robust and context-aware approach for depression detection in social media text. These outcomes emphasize the potential of automated systems to support early identification of mental health issues, offering scalable solutions for intervention and continuous monitoring, ultimately contributing to improved mental health awareness and timely support.

Future research can focus on expanding the dataset to include multilingual and cross-platform social media content, enhancing the generalizability of depression detection models. Incorporating multimodal data, such as images, videos, and user interaction patterns, can improve context understanding and detection accuracy. Advanced transformer-based architectures, including hybrid ensembles of BERT variants and graph neural networks, may capture complex semantic relationships more effectively. Real-time detection pipelines can be developed for continuous monitoring and early intervention. Further exploration of attention mechanisms and explainable AI techniques, such as Grad-CAM and SHAP, can provide insights into model decisions and increase transparency. Additionally, integrating longitudinal analysis to track behavioral patterns over time could enhance predictive capabilities and support proactive mental health support strategies.

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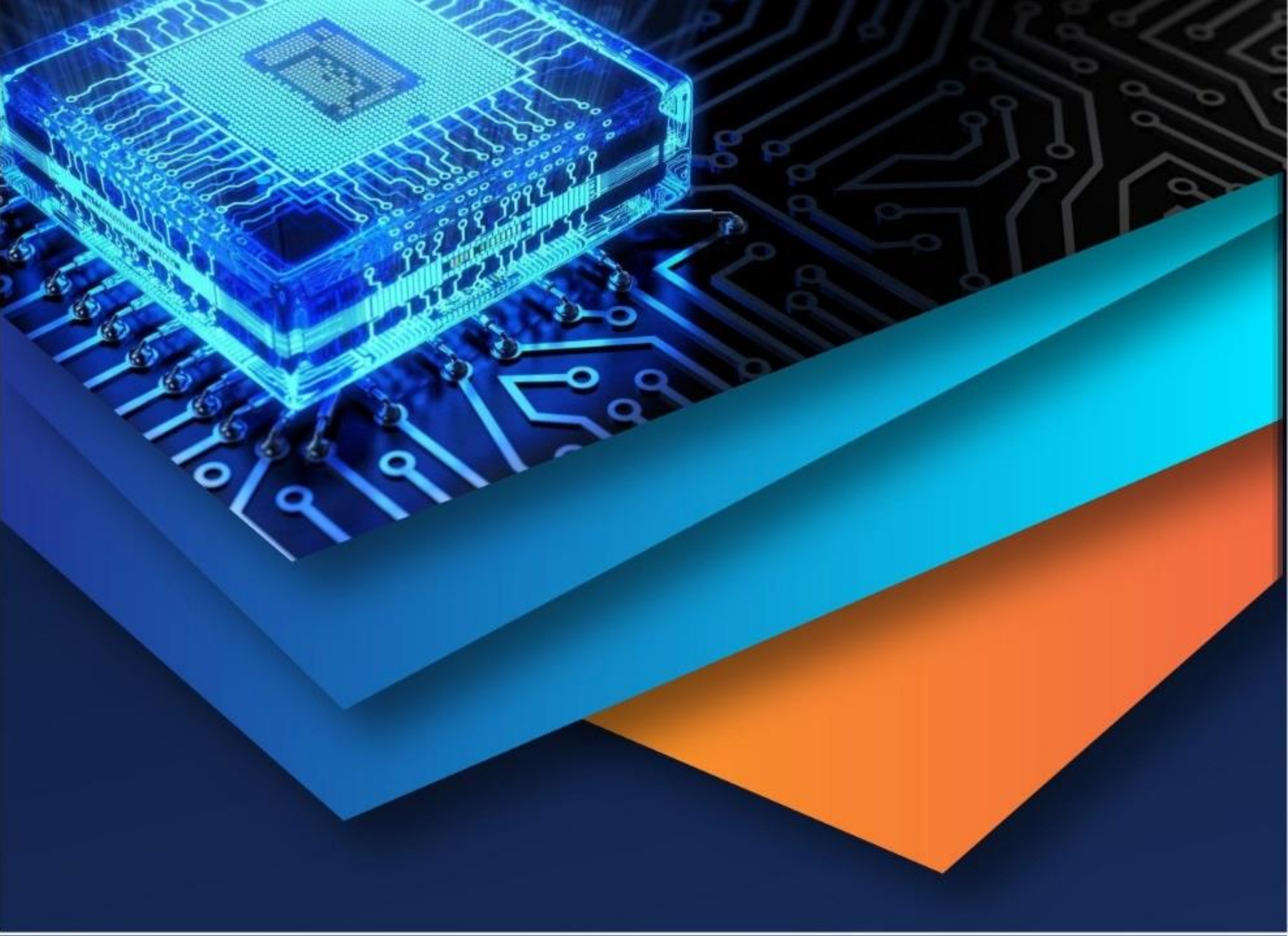

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