Hybrid Approach for Enhanced Depression Detection using Learning Techniques

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***Abstract*—According to the World Health Organization (WHO), depression affects over 350 million people worldwide, making it the most common health problem. Depression has numerous causes, including fluctuations in business, social life, the economy, and personal relationships. Depression is one of the leading contributors to mental illness in people, which also has an impact on a person's thoughts, behavior, emotions, and general wellbeing. This study aids in the clinical understanding of patients' mental health with depression. The primary objective of research is to examine learning strategies to enhance the effectiveness of depression detection. The proposed work includes 'Extended- Distress Analysis Interview corpus' (E-DAIC) label dataset description and proposed methodology. The membership function applies to the Patients Health Questionnaire (PHQ8_Score) for Mamdani Fuzzy depression detection levels, in addition to the study of the hybrid approach. It also reviews the proposed techniques used for depression detection to improve the performance of the system. Finally, we developed the Ensemble-LSRG (Logistic classifier, Support Vector classifier, Random Forest Classifier, Gradient boosting classifier) model, which gives 98.21% accuracy, precision of 99%, recall of 99%, F1 score of 99%, mean squared error of 1.78%, mean absolute error of 1.78%, and R^2 of 94.23.**

Keywords*—Depression detection; machine learning; extended-distress analysis interview corpus; ensemble-LSRG model; mamdani fuzzy

I. Introduction

Depression is the most common mental disease in the world. Causes of disruption include the emotion experience, lack of communication, human behavior, and social media problems [1]. Human existence is present on the internet and in social media, just as it is in daily life. Additionally, communication is getting better every day. Unknown people can communicate with one another online, yet there are also drawbacks to social media and the internet. Anorexia and bipolar depression affect millions of individuals globally, making depression one of the worst problems in the world [19], and [25]. Over 350 million people worldwide are affected by depression, and it's the most common health problem, according to the World Health Organization (WHO) [26], [27], and [12]. According to research on the causes of depression, the risk of suicide increases more than 30 times among those in generally good health [27] and [29].

Despair triggers numerous events. Every day in the surrounding area, people can observe the prevalence of suicidal situations and other mental illnesses [11] that are also influenced by depression. For example, in today's society, stress from the daily workload significantly raises the risk of developing it. According to a poll on depression, the following symptoms appear virtually daily for two weeks: Depression or a loss of mood, a decline in enthusiasm for the activity, suicidal thoughts, and a sense of hopelessness [19]—other factors, such as genes and family history, can also contribute to depression [23]. All different kinds of men and women of all ages struggle with this issue. According to the WHO, depression affects 350 million individuals globally [26], [27], and [12]. According to research on the causes of depression, the risk of suicide increases more than 30 times among those in generally good health [27], [29], and [31].

Depression can be detected by utilizing learning approaches using the system's multimodal resources. The system's objective is to offer many modalities on the same platform in order to increase accuracy and the techniques for detecting emotions, such as sentimental analysis and speech prosody. 12% and 6.6%, respectively, of men and women are seeing an increase in depression [12]. Humans communicate their emotions more frequently in daily life through speech, social media, blogs, and chat rooms. The study offers the voice activity detector, speech emotion recognition, and text emotion recognition for text-based data [24], [26], and [27]. Face analysis can help identify of depression [21], and [27]. The merger of all modalities can aid in increasing the system's accuracy [22]. According to a 2019 survey, there were 1,39,123 suicide-related deaths in India, and the national rate of self-destruction continued to be 10.4 (calculated per 1 lakh people), as stated in Chapter 2 of the National Crime Record Bureau, for example. Recently, 'Sushant Singh Rajput' attempted suicide due to depression [1]. The goal of this system is to create a hybrid modal system [9] that will help society and medical professionals diagnose and track depression. This study utilized ensemble learning to learn from PHQ8 data in order to get the correct positive results [30].

In this section, include an introduction and motivation for the study, as well as a general overview of the study. In the second section, it includes related work of the study, including existing work related to the study, the gap analysis, as well as the key issues and challenges part. The third section outlines the recommended strategy for improving system performance, the dataset description, and algorithmic details; the fourth section includes the result and discussion part. The conclusion and future scope are covered in the final part.

II. Related Work

As per the literature survey observed that the following related work:

The MSN (Multi-scale Spatiotemporal Network) model, put forth by Wheidima Carneiro de Melo, integrates face data associated to depressive behavior from image [2]. Models only pick up irregularities associated with people's facial expressions. This work made use of the Audio-Visual Emotion Recognition Challenge (AVEC2014) dataset. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) components influence the results. The DMVM (Deep Mood Architecture with Multi View Machine) model is suggested by Xiaohang Xu and Hao Peng and is used to identify depression [3]. Hospitals preserve patient health information in accordance with privacy concerns. This information cannot be used for a centralized machine learning in the diagnosis of depression. At that point, federated learning is crucial for identifying depression. Accuracy serves as the primary criterion for analyzing outcomes in comparisons. To classify the data into five categories (healthy, smooth, pleasant, neutral, and serving), Kaining Mao, Wei Zhang, and Deborah Baofeng Wang developed a model on the Oz dataset using the Distress Analysis Interview Corpus Wizard [4]. The final result was based on the F1 score, accuracy, precision, and recall. They used the following networks: Bidirectional BI-LSTM+FC, LSTM+ Time-distributed Convolutional Neural Network TCNN, Long Short Term Memory LSTM + FC, and BI- LSTM+ TCNN.

Shallow (EdgeER) and deep models are used by Shuai Ding, Zi Xu, Yaping Wang, Lina Qu, Yinghui Li, Yao Yu, Xiaojian Li, and Shanlin Yang et al. *[5]. Deploy the deep model (C-DepressNet) to cloud servers and the shallow model (EdgeER) to edge servers. EdgeER can instantly identify unfavorable sentiment in user data. High-precision analyses of depression levels are performed using depth models. BDI-II score values are finally categorized as follows: no depression, mild, moderate, or severe depression. Pushpak Bhattacharyya, Soumitra Ghosh, and Asif Ekbal, et al. [6], on multi-model multitasking systems. This work includes multi-model social network profiles that leverage deep learning to retrieve metadata (e.g., user location, photo, and description). Work on image collections and emotionally charged datasets for outcome analysis. The model's accuracy and F1 score dictate the result. Conv + Maxpool Layer, Shared Multilayer Perceptron (MLP), Task-Specific MLP, Output Layer, Hidden Activation, Output Activation, Batch Size, Epoch, Dropout, Loss, Optimizer, etc. are some of the parameters. Lei Tong, Zhihua Liu, Zheheng Jiang, Feixiang Zhou et al. proposed a method for identifying depressed Twitter users [7]. “Cost-sensitive Boosting Pruning Trees” (CBPT) gets classification results using a variety of technique. "Cost-sensitive Boosting Pruning Trees" (CBPT) uses a range of methods to provide classification results. Including "Discrete Adaboost, Real Adaboost, XGboost, LogitBoost, LightGBM, and HiGB", various methods are used when comparing to the UC Irvine (UCI), the machine learning repository. The eight boosting classifiers' accuracy and F1 scores serve as the foundation for the final analysis.

Using the SH2 data sets and the “Distress Analysis Interview Corpus/Wizard-of-Oz collection” (DAIC-WOZ), Zhaocheng Huang, Julien Epps, Dale Joachim, and others conducted tests [8]. The algorithm's F1 rating is the foundation for the ultimate rating. Among the groundbreaking features of this study are "g(lottis)," "p(eriodity), "s(onorant"), "f(ricative), "v(oiced fricative), and "b(ursts)". Erik Cambria, Shaoxiong Ji, Qian Chen, and Luna Ansari examined a text classifier that was taught to identify depression. An assessment matrix is used to assess classification systems. Precision, recall, F1 score, and precision make up the evaluation matrix. A unique automatic depression detection ADD (Temporal dilated convolutional network - TDCN and feature wise attention - FWA) model proposed by Yanrong Guo, Chenyang Zhu, and et al. [10] suggests data collecting based on the visual cues captured throughout the interview process. Other modalities, including as text and audio, could be used in this study to enhance the system's functionality. The ultimate outcome is based on factors like as accuracy (0.857), recall (0.91), precision (0.733), and F1 score (0.85). Study based on sub-emotions (BoSE), Late Fusion Methods by Mario Ezra Aragon et al. In order to improve depression identification, this study combines static and dynamic representations of early and late fusion techniques. Processing solely text-based data. Privacy about certain data. It is forbidden to misuse and handle sensitive information improperly. Factors such as the F1 Score of 0.64, Precision of 0.67, and Recall of 0.61 influence the final outcome.

Electroencephalogram (EEG) signal decomposition for depression identification by Jian Shen, Xiaowei Zhang, Bin Hu, Gang Wang, et al. [12]. It illustrates how the human brain functions. This piece of art illustrates how the human brain functions. Electroencephalogram (EEG) databases have accuracies ranging from 83.27% to 85.19% to 81.98% to 88.07% for each dataset. Usman Ahmed, Jerry Wei Lin, and others [13] proposed the BI-LSTM, which has received much attention and uses unlabeled forum text and social media data to boost the rate of diagnosing depressive symptoms from online data. These studies' drawbacks include dealing only with textual data and illiteracy. Accuracy and Cohen Kappa metrics are used to compare results. Studying the self-attention graph pooling-soft label (SGP-SL) model are Tao Chen, Yanrong Guo, and colleagues [14].

In this study, soft labeling was employed together with an experiment using the ‘MODMA’ dataset, a multi-modal open dataset for mental-disorder investigation that served as an efficient model in many ways. Another area of investigation in the feature work is the issue of incomplete modalities and the identification of major depressive disorder (MDD). The final result depends on parameters like, Accuracy= 84.91%, Precision= 80.77, Recall= 87.50, F1-Score=84. A study on LSTM, CNN, and hybrid (CNN + LSTM) models was conducted by Mudasir Ahmad Wani, Mohammad A, and colleagues [15] to examine variables including precision, accuracy, and F1 score. The term frequency-inverse-document frequency (TF-IDF) based characteristics and Word2Vec were used in this investigation. We must continue to develop on the multiplication corpus because it only covers the English language. Study on logistic regression by Jianxiu Li, Nan Li, Xuexiao Shao, et al. [16]. Microstate Parameters: Duration, Occurrence, and Time Coverage performed well in this investigation at detecting MDD. Restriction on the number of participants with MDD and healthy controls (HC). Large data sets are necessary to demonstrate the study's statistical power.

Study on the Mutual Information Based Fusion Model (MIBFM model) by Jing Zhu, Changlin Yang, et al. [17]. This study put forth the model that is used to correlate the signals from the pupil area and the EEG. The National Key Research and Development Program of China (NKR&DP of China) is funding this work. To carry out activities, data gathering and dataset enrichment are necessary. Mild depression and normal control require binary classification. Deep Convolutional Neural Network (DCNN) and Deep Neural Network multimodal investigation of depression by Le Yang, Dongmei Jiang, and Hichem Sahli [18]. In AVEC2016, support vector machines and random forests are both employed for classification. They used text documents, audio data, and video data for this endeavor.

Studies on identifying psychiatric diseases such anorexia and depression by Mario Ezra Arag'n, A. Pastor L'opez-Monroy, Luis C. Gonz'alez, et al. [19]. Users of social media have unfortunately developed depression as a result of their use. Anorexia and Depression Sentiment Distribution solely use this information for study and analysis. Data that should not be shared. Studying depression during and after pregnancy, Kristen C. Allen, Alex Davis, and Tamar Krishnamurti [20] conducted a study to inadvertently detect perinatal psychosocial concerns. This study examined both happy and negative feelings as well as a lack of relationship support to identify emotions, despair, and sentimental analysis.

III. Proposed Work

The proposed work of the study including the dataset Description, the proposed methodology and algorithmic detail:

A. *The Dataset Description*

Semi-clinical interviews prepare the Extended Distress Analysis Interview Corpus (E-DAIC) dataset. The dataset is designed to support the psychological distress condition such as anxiety, depression and post-traumatic stress disorder. These interviews were collected as part of a larger effort to create a computer agent that interviews, people and identifies verbal and nonverbal indicators of mental illness. An animated virtual interviewer called Ellie conducts the interviews. A subset of session are collected in a wizard-of-Oz (WoZ) setting, were the virtual agent is controlled by a human interviewer (wizard) in another room [30].

The Dataset is classified into training, development, and test dataset while preserving the overall speaker's diversity -- in terms of age, gender distribution, and the eight-item Patient Health Questionnaire (PHQ-8) scores -- within the partitions. Whereas the training and development sets include a mix of WoZ and AI scenarios, the test set is solely constituted from the data collected by the autonomous AI [39]. Sessions with IDs in the range [300,492] are collected with WoZ-controlled agent and sessions with IDs [600,718] are collected with an AI-controlled agent [30].

B. *Proposed Methodology*

The proposed methodology of the study on the E-DAIC (Extended – Distress Analysis Interview corpus) label dataset is shown in Fig. 1.

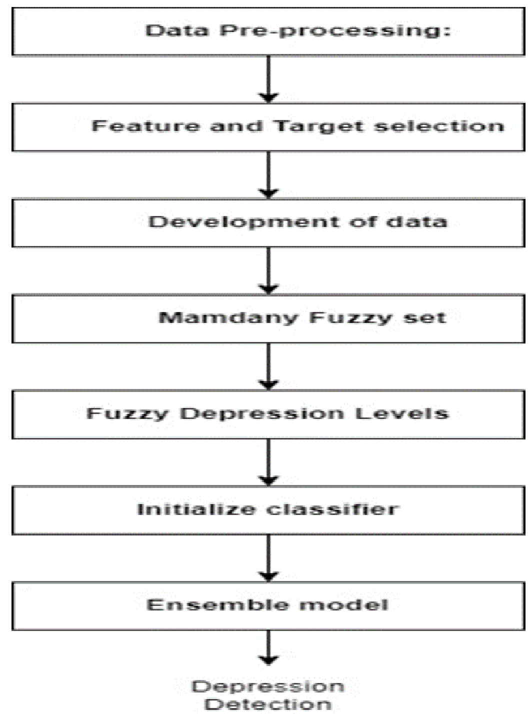

Fig. 1. Proposed methodology for the depression detection system using ensemble model.

The labeled dataset contains data from 275 participants. Specifically, the train_split.csv contains records from 163 participants, the test_split.csv contains records from 56 participants, and the dev_split.csv contains records from 56 participants. The methodology follows the following steps,

1) Data pre-processing: In data pre-processing it upload the train_split.csv, test_split.csv and dev_spit.csv from the E-DAIC Dataset. Pre-processing of the data include the data cleaning, data normalization and finding the missing values. Additionally, data is augmented and increase the data size with five times.

$$X=imputer.fit\_transform(X) \quad (1)$$

where, X is the feature set vector.

By using Eq. (1) to handle the missing values from feature sets.

2) Feature and target selection: Feature selection is the very important of this study. This can be done by observing the correlation between the variable. Target selection also be important for this study.

3) The Development of data: The Development of the data combine train_split and dev_spit dataset for model development.

4) Define mamdani fuzzy se: In Mamdani fuzzy logic define the membership function for PHQ8_Score and create the output variable. In the fuzzy set define the membership function for depression severity also define the rules for classification for four classes then define create the fuzzy control system.

5) Fuzzy depression levels: Apply fuzzy logic to calculate Mamdani fuzzy depression level.

MamdaniFuzzyLevel=apply_fuzzy_logic (PHQ_Score) (2)

6) Initialize classifier: In this study used no of classifier like logistic_regression, support classifier, Random_Forest_Classifier, Gradient_Boosting_Classifier to the ensemble model.

7) Ensemble model: Define ensemble model for hybridization and train it by training data to improve the performance of the system.

ensemble_model=VotingClassifier (estimators=[('lr', clf1), ('svc', clf2), ('rf', clf3), ('gb', clf4)], voting='soft') (3)

ensemble_model.fit (train_X, train_y) (4)

Where,

X is feature set y is the target,

lr is logistic classifier,

svc is support vector machine classifier,

rf is random forest classifier,

gb is gradient boosting classifier.

By using Eq. (3) and Eq. (4) define and train the ensemble model.

8) Prediction and evaluation of the model: Make predictions using the trained ensemble model.

Calculate accuracy, confusion matrix, and visualize the confusion matrix.

y_pred = ensemble_model.predict(X_test) (5)

accuracy = accuracy_score(y_test, y_pred) (6)

cm=confusion_matrix(y_test, y_pred) (7)

By using Eq. (5), we can predict the depression detection using the ensemble model. Eq. (6) used to calculate the accuracy of the model and Eq. (7) used to generate the confusion matrix of the predicted values and actual results.

IV. Results and Discussions

In this study execute the whole system using the ensemble LSRG (Logistic regression, Support vector classifier, random forest classifier and the gradient boosting) model to improve the performance of the system.

The above Fig. 2 shows the membership function of the fuzzy system with respective to the phq_score. The depression detection system, including only four levels of depression, i.e. "No Depression", "Mild Depression", "Moderate Depression", and "Severe Depression". The Fig. 2. Shows the membership for low, medium and high phq_score.

In Fig. 3, show that the confusion matrix of "Linear Regression model" and "Ensemble–LSRG model". As per figure, the "Ensemble-LSRG model" is less confuse than the "Linear Regression model". Less confuse means the "Ensemble-LSRG model" give the high accuracy. The accuracy required to calculate the accurate depression level.

In Fig. 4, show that the confusion matrix of "Support Vector Machine" and "Ensemble–LSRG model". As per figure, the "Ensemble-LSRG model" is less confuse than the "Support Vector machine". Less confuse means the "Ensemble-LSRG model" give the high accuracy. The accuracy required to calculate the accurate depression level.

In Fig. 5, show that the confusion matrix of "Random Forest classifier" and "Ensemble–LSRG model". As per figure, the "Ensemble-LSRG model" is less confuse than the "Random forest classifier". Less confuse means the "Ensemble-LSRG model" give the high accuracy. The accuracy required to calculate the accurate depression level.

In Fig. 6, show that the confusion matrix of "Gradient boosting classifier" and "Ensemble–LSRG model". As per figure, the "Ensemble-LSRG model" is less confuse than the "Gradient boosting classifier". Less confuse means the "Ensemble-LSRG model" give the high accuracy. The accuracy required to calculate the accurate depression level.

In Fig. 7, show that the confusion matrix of "Convolutional Neural Network" and "Ensemble–LSRG model". As per figure, the "Ensemble-LSRG model" is less confuse than the "Convolutional Neural Network". Less confuse means the "Ensemble-LSRG model" give the high accuracy. The accuracy required to calculate the accurate depression level.

In Fig. 8, displays the confusion metrics of depression detection using Recurrent Neural Network. From the observation of the diagram, it is evident that the "Ensemble (LSRG) model" is less confused compared to other techniques. "Less confusion" implies that the "Ensemble-LSRG model" provides higher accuracy. Accuracy is necessary to calculate the precise level of depression.

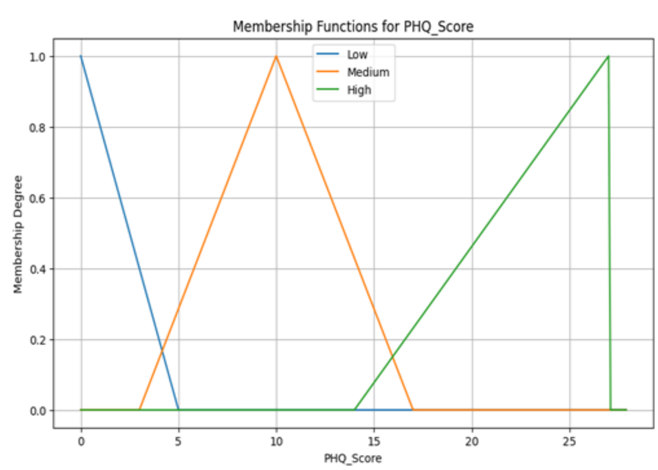

Fig. 2. Membership vs phq_score.

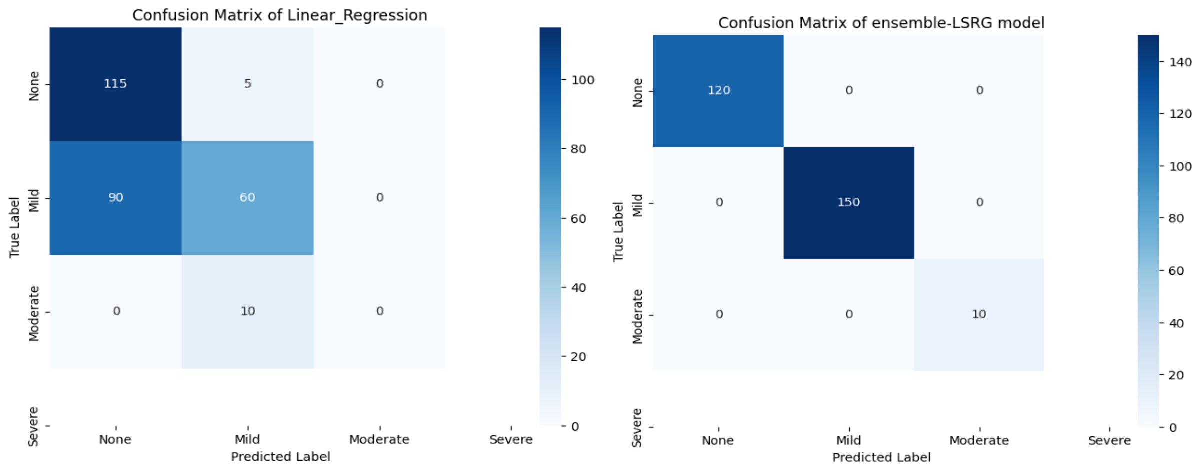

Fig. 3. The Confusion matrix of linear regression and ensemble- LSRG model.

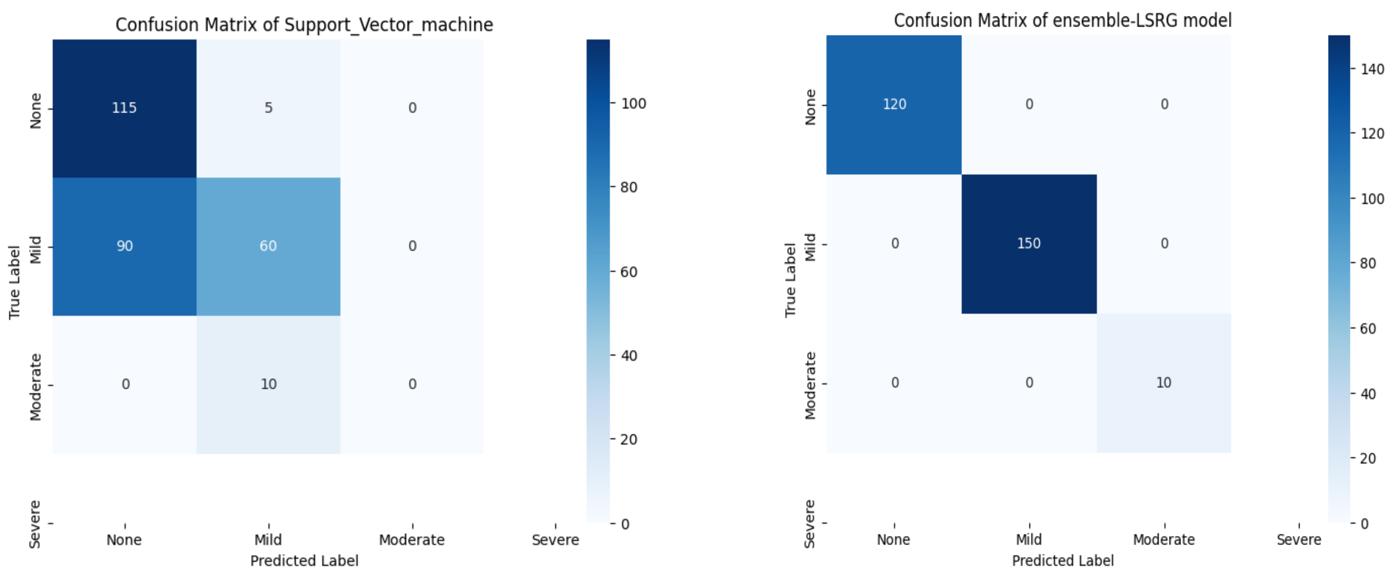

Fig. 4. The Confusion matrix of support vector machine and ensemble- LSRG model.

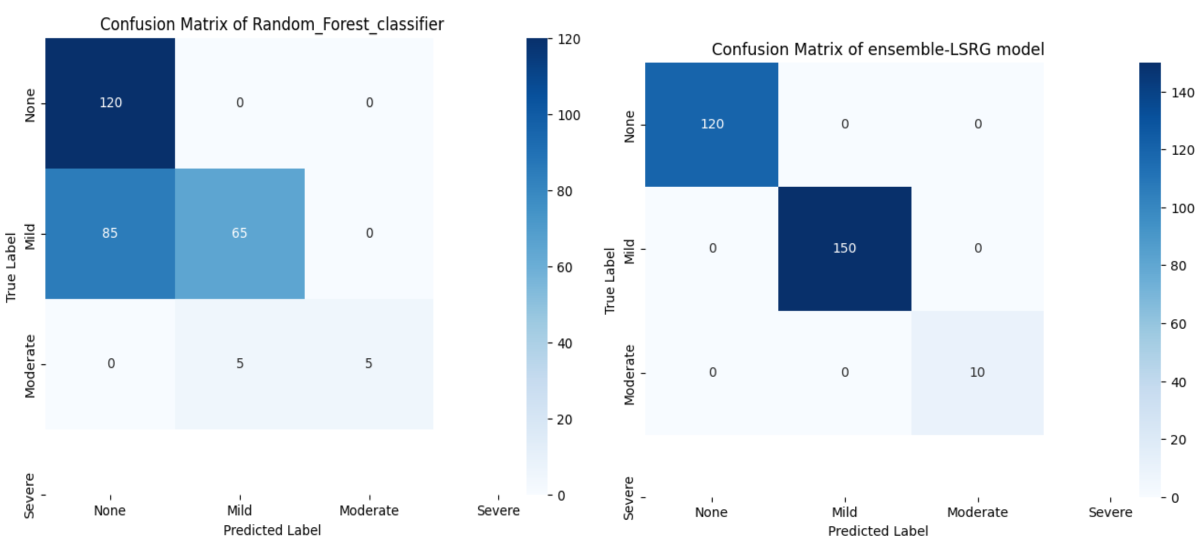

Fig. 5. The confusion matrix of random forest classifier and ensemble- LSRG model.

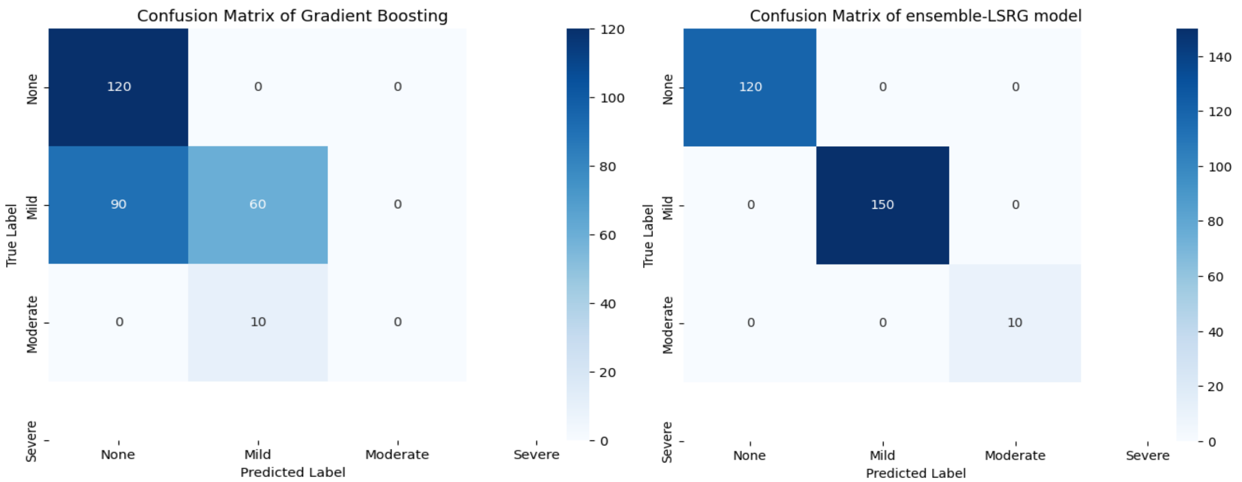

Fig. 6. The Confusion matrix of gradient boosting and ensemble- LSRG model.

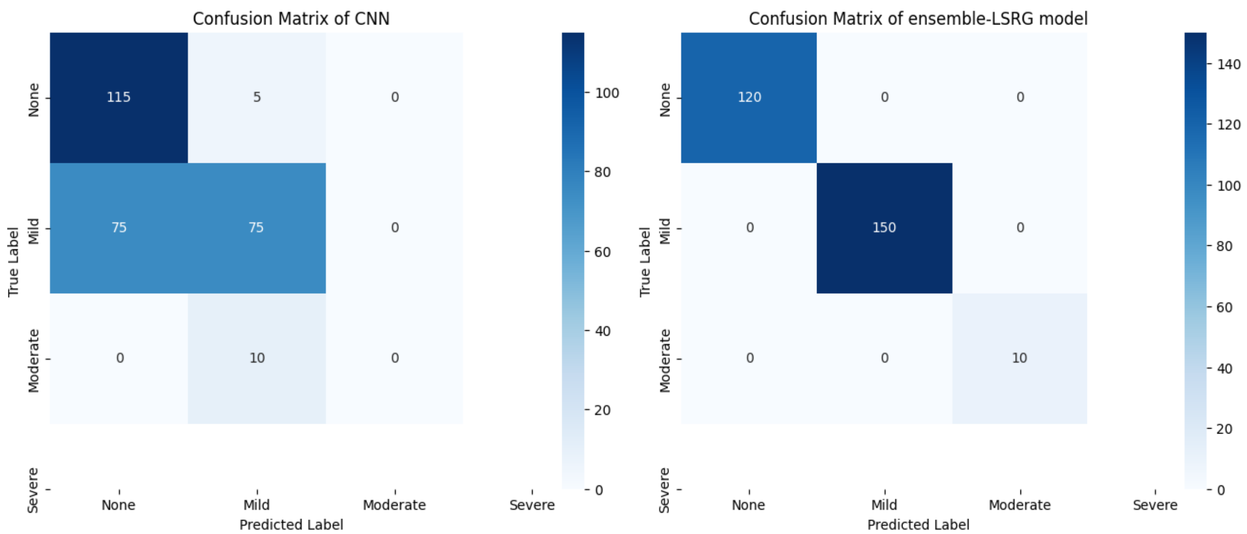

Fig. 7. The Confusion matrix of CNN and ensemble- LSRG model.

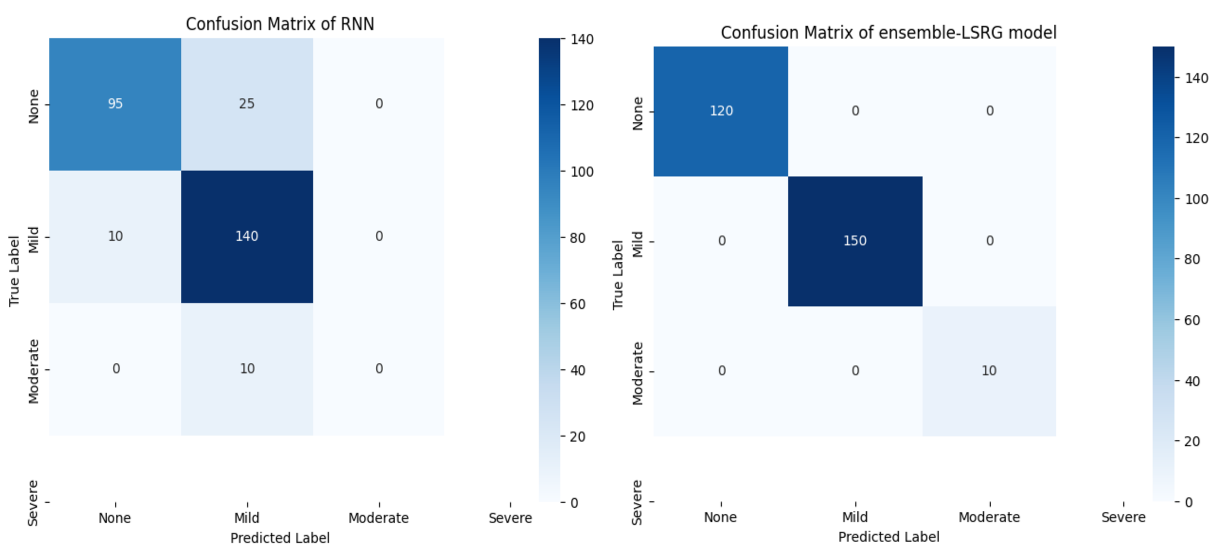

Fig. 8. The Confusion matrix of RNN and ensemble- LSRG model.

TABLE I. COMPARISON CHART OF EXPERIMENTAL ANALYSIS OF THE DEPRESSION DETECTION SYSTEM USING ENSEMBLE (LSRG) MODEL

Sr.	***Learning Technique***	***Accuracy in (%)***	***Precision in %***	***Recall in %***	***F1 Score in %***	***Mean squared error in %***	***Mean Absolute error in %***	***R2 score***
1	Linear regression	62.5%	67.00%	62.00%	59.00%	15.42%	30.57%	50.21%
2	Support vector Machine	62.5%	67.00%	62.00%	59.00%	16.32%	31.43%	47.31%
3	Random Forest	53.57%	77.00%	56.00%	53.00%	03.78%	01.31%	87.80%
4	Gradient boosting	64.28%	70.00%	64.00%	60.00%	01.25%	03.94%	95.96%
5	Convolutional Neural Network (CNN)	42.85%	19.00%	43.00%	26.00%	62.50%	58.92%	70.6%
6	Recurrent Neural Network (RNN)	78.57%	76.00%	79.00%	77.00%	21.42%	21.42%	30.86%
7	Ensemble- LSRG model(Ours)	98.21%	99.00%	99.00%	99.00%	01.78%	01.78%	94.23%

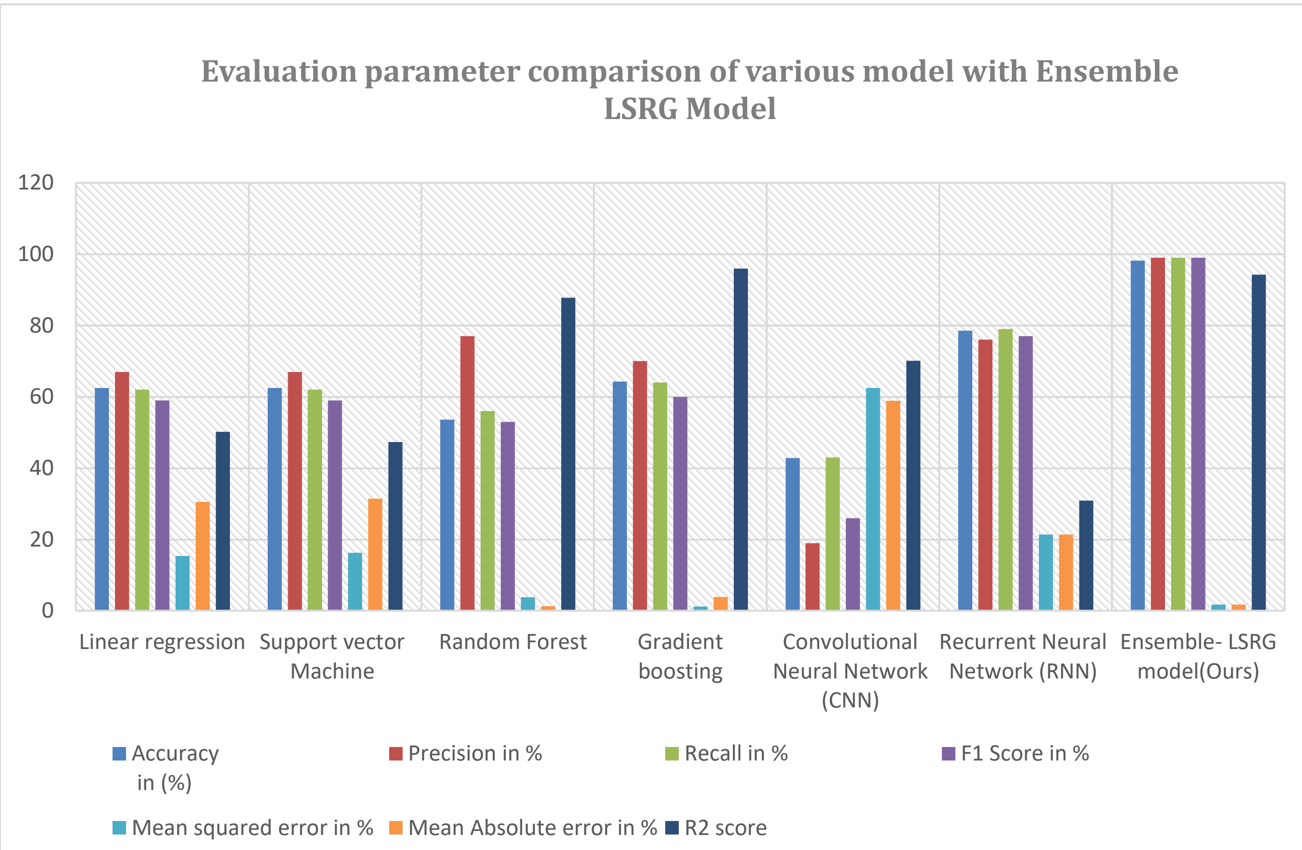

Fig. 9. Evaluation parameter comparison of various model with ensemble LSRG model.

Table I and Fig. 9 shows the analysis of performance of the depression detection system using different machine learning algorithm and Ensemble –LSRG model using various parameters likes, accuracy, precision, recall, F1 score, mse, mae, and R^2 score. As per table and Fig. 9. shows that the linear regression model having accuracy of 62.5%, precision of 67%, recall of 62%, F1 score of 59%, mean squared error of 15.42%, mean absolute error of 30.57% and R^2 score is 50.21%. The second model is a support vector machine with an accuracy of 62.5%, precision of 67%, recall of 62%, F1 score of 59%, mean squared error of 16.32%, mean absolute error of 31.43%, and R^2 of 47.31%. The third model is a random forest with an accuracy of 53.57%, precision of 77%, recall of 56%, F1 score of 53%, mean squared error of 03.78%, mean absolute error of 1.31%, and R^2 of 87.80%. The fourth model is gradient boosting with an accuracy of 64.28%, precision of 70%, recall of 64%, F1 score of 60%, mean squared error of 01.25%, mean absolute error of 03.94%, and R^2 of 95.96%. The fifth model is a Convolutional Neural Network with an accuracy of 42.85%, precision of 19%, recall of 43%, F1 score of 26%, mean squared error of 62.50%, mean absolute error of 58.92%, and R^2 of 70.6%. The next model is a Recurrent Neural Network with an accuracy of 78.57%, precision of 76%, recall of 79%, F1 score of 77%, mean squared error of 21.42%, mean absolute error of 21.42%, and R^2 of 30.86%. The last model is the Ensemble-LRGS model (Ours) with an accuracy of 98.21%, precision of 99%, recall of 99%, F1 score of 99%, mean squared error of 1.78%, mean absolute error of 1.78%, and R^2 of 94.23%.

In discussion of research the Fig. 9, shows linear regression model having moderate performance with accuracy, precision, recall, and F1 score all around 60% also mean squared error and mean absolute error are relatively high, suggesting it might not fit the data well. The second model support vector machine also give the similar performance as per linear regression model so it is also not significantly better or worse. The third model is random forest which gives the high precision rate 77% but the accuracy is lower as compare to first two model. The forth model is gradient boosting show the best performance among individual model with high accuracy 64. 28% and precision 70%. The fifth model perform relatively poorly as compare to other models with lower accuracy, precision, recall and F1 score, it means high mean squared error and mean absolute error indicating poor fit of data. The sixth model is recurrent neural network shows high accuracy 78.57% and precision 76% indicating its performing better than most individual model. The last model Ensemble-LSRG model (Ours) demonstrate the outstanding performance across all metrics with very high accuracy, precision, recall and F1 score, additionally it has lower mean squared error and mean absolute error among all models indicating the data is fit extremely well.

V. Conclusion and Future Scope

The study includes research work and various learning techniques and algorithms aimed at identifying research gaps. Additionally, it examines previous research on depression detection [28] and systems. This work will illustrate different depression detection systems, key issues, and challenges. Furthermore, it investigates a proposed methodology to enhance the system performance. The system achieves high accuracy compared to existing algorithm techniques. In this study, the system achieves 98.21% accuracy, precision of 99%, recall of 99%, F1 score of 99%, mean squared error of 1.78%, mean absolute error of 1.78%, and R^2 of 94.23% for the Ensemble LSRG model (Ours). In future research, the method to detect depression using a learning approach will be implemented. Additionally, performance metrics for early depression detection will be confirmed through experimentation analysis. Finally, the performance of the proposed algorithm will be evaluated against other popular depression detection algorithms to validate the results.

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