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A Comparative approach of Depression Detection: A state of Art

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Abstract:

Depression is an unconscious state of mind; it directly affects the mental health condition of patients, so it is required to accurately detect with a certain time to prevent severe depression. Depression detection with traditional approaches includes the patient's interviews and self-reporting to doctors or psychotherapists, but this approach faces challenges like time consumption and subjectivity. Another approach is to detect depression by using some computational techniques, including ‘machine learning (ML)’, ‘deep learning’, ‘natural language processing’, and also some wearable technologies or devices. The study compares the hybrid ensemble model and the late fusion method with other classifiers that are used for depression detection based on various performance parameters, like ‘accuracy’, classification report, ‘mean squared error’, and R2 score , etc. This study also discusses some ethical terms, such as the privacy of patient data and the risk of misdiagnosis. The study highlights the multimodal approach of various modality to build an effective and personalized system for depression detection.

Keywords: Machine learning, natural language processing, wearable technology, mental health, multimodal data, ethical considerations, sentiment analysis, social media analysis.

1. INTRODUCTION

Depressive disorder (Depression) is a common mental health issue globally. According to the ‘World Health Organization (WHO)’, 3.8% of the population affected by depression. Suicide is the fourth-leading cause of deaths in 15-29-year-olds. There are multiple depressive symptoms, like a person feeling alone, affecting mood, feeling sad, and being irritable [1]. The depression can cause multiple problems in life, community, work, school, and home also [1]. The surrounding culture is also reasonable for depression progression, so it needs to implement appropriate language and try to avoid labels such as ‘crazy', 'mad', 'mental', ‘mad’, ‘mental’ etc. [2]. The study requires cultural transformation to support the mental health of the patients [2].

Beck Depression Inventory (BDI) tool is used to rate the severity of depression. MG-CFA supported invariance across gender, suggesting that the same BDI-II construct could be applied to both female and male adolescents. This study provides evidence that the BDI-II could be used as a uni-dimensional measure of depressive symptoms in adolescents by researchers and clinicians [3]. The mental health disorder can also be part of depression. As per estimating, the mental health disorder will contribute to a loss of USD 16 trillion globally up to 2030 [4]. There are multiple techniques that replace traditional techniques or diagnosis methods, like machine learning techniques, deep learning techniques, natural language processing, single modality techniques, and multimodality techniques [5], [6].

Recently, the application of artificial intelligence to the mental health care system has achieved a higher level of excellence [7]. The researcher revives the multidisciplinary study approach based on patient data, like sentimental analysis using natural language processing (NLP), predictive analysis to predict the correct depression level of patients using machine learning (ML), and deep learning (DL) for mental healthcare delivery [7]. The study also includes common ethical issues, cyber security, and different diversity in data analytics, language barriers, and cultural diversities that also affect the mental health condition. The study uses historical data of patients for predictive analysis in the medical healthcare system; also, patient screening activities use the subset of artificial intelligence (AI) such as machine learning (ML) and deep learning (DL) to analyze and explore the patient healthcare dataset [7]. Certain research approaches also involve optimizing word embedding for improved data classification in depression prediction [8]. The study conducted a comparative analysis of existing deep learning (DL) algorithms for detecting patient depression using Twitter data at the user level, specifically on the 'CLPsych2015' and 'Bell Let's Talk' datasets, to compare the performance of convolutional neural networks (CNN) with recurrent neural networks (RNN) [8]. The study 'predicting depression via social media' also on the twitter data to diagnosis of major depression level in individual patient based on psychometrics instruments [9]. The exploration of study [10] include 40 adult patients depression data of daily life behavior using mobile phone global positioning system (GPS) and sensors for identification of depression data. The all features are extracted from the mobile sensor data, GPS and mobile phone usage [10].

This study aims to compare the different existing depression detection techniques with a multimodal system. The study focuses on integrating different modality with an effective method, i.e., the late fusion method. This study also highlights the strengths and limitations of each approach and modality. The implementation of the system it used various different modalities like audio, visual, and textual modality. The study integrate all modalities using late fusion methods. The study calculate the results of each audio and visual modality using a hybrid ensemble LSRG ('Logistic Regression', 'Support Vector Classifier', 'Random Forest Classifier', and 'Gradient Boosting Classifier') and compare them with different classifiers. The introduction of paper included the background of depression and diagnosis of depression using multiple studies. The second section literature review included different approaches and methodologies. The Methodology for Comparative Analysis include comparison parameters like performance metrics, data source and datasets. Results and Discussion include present results and charts and last session is the conclusion.

2. Literature Review

Depression detection in which identify depressive symptom in individual patients through various technologies, algorithms, methodologies and tools. The related work of comparative approach of depression detection of study as follows:

The study work includes early detection of depression and prevent mental health issues [11]. The system developed epidemiology in preparation of mental health disorder and detect depression initially. The early depression improve mental health condition, prevention of complications, improve outcomes of treatments and reduced the medical cost [11]. As per historical and evaluation techniques, early depression firstly calculated by Beck at 1961 based on self-reported questionaries' and clinical assessment i.e. the Beck Depression Inventory, and secondly Koneke at 2001 i.e. the Patient Health Questionnaire [12], [13].

The above approaches require active participation for quaternaries and clinical reports for patients. So, there are multiple advanced technologies are innovate for automated and passive detection of depression i.e. artificial intelligence (AI) [14]. The 'artificial intelligence (AI)' has advance development contain of 'machine learning (ML)' and 'natural language processing (NLP)' algorithm for better depression detection accuracy and prediction [14].

The studies based on linguistic-based approach analyze different language patterns to detection and prediction of depression [15]. The natural language processing (NLP) mostly use for sentimental analysis, lexical techniques and language marker. The study worked on people experiencing depression and use a more negative word or language also pronouns. So, its effect on surrounding culture [15], [16]. Another study based on the same approach, i.e. linguistic based approach work on analysis of Twitter and Reddit dataset. The study identify most useful neural network in natural language processing [17].

Depression detection based on physiological signal based technique leverage signals from physiological resources, such as ‘electroencephalography’ (EEG) and electrocardiography (ECG), to detection of the depressive state of mind. Studies have found that EEG patterns can reflect mental health condition and state also, with depressive patients often showing specific brainwave abnormalities for depressive conditions [18]. Another study also examine variability of heart rate, it is capture through ECG. This study also correlate with mood and it can help to detect depression of patients [19].

The study introducing AI and ML-Driven approaches for an applied ‘machine learning model’ and ‘deep learning model’ to analysis of vast amount data, it analyzed complex patterns in text, images, or biometric data to predict depression risk. ‘Support vector machines (SVMs)’, ‘neural networks’, and ‘deep learning architectures’ are frequently employed, sometimes in combination with NLP or signal processing techniques [20]. These methods enable scalable, non-invasive depression screening and have shown promise in applications like mobile apps and online platforms.

Several studies have benchmarked various methods of depression detection using different datasets and models: The work used social media data to study linguistic markers of depression, comparing traditional regression models with more recent ML methods on datasets like Twitter [15]. ‘Saeb’ used mobile sensor data and applied ML models to detect depression from behavioral patterns, demonstrating the effectiveness of SVMs and neural networks on the dataset they collected [10]. ‘CLPsych2015’ and ‘Bell Let’s Talk’ datasets have been frequently used in studies comparing different NLP models, including ‘convolutional neural networks (CNNs)’ and ‘recurrent neural networks (RNNs)’, for detecting depressive language [17]. The most comparative studies face challenges due to dataset diversity, data privacy concerns, and limited generalizability across populations [21]. Additionally, cultural and linguistic differences impact how depressive symptoms manifest in language or behavior, making cross-cultural comparisons challenging [22].

The latest Innovations in Detection Algorithms and Models: Recent advancements in AI have introduced innovative approaches like transformer models (e.g., BERT and GPT) for processing language and large datasets, which enhance detection accuracy. These models excel in identifying subtle linguistic patterns and contextual meanings, which are critical for understanding depressive language [23]. Wearable devices, such as smart watches, are increasingly used to monitor physiological signals, integrating AI to predict mood changes and detect depressive states in real-time [24]. Additionally, multimodal models that combine text, audio, and visual data are gaining traction, offering more holistic insights into depressive behavior [25]. Applications like ‘Mindstrong’ and ‘Woebot’ employ AI-driven algorithms to monitor mood and provide immediate support based on depressive symptom tracking. Advances in telemedicine are also making these tools more accessible, expanding reach to underserved populations [26]. The survey of depression detection conducted to learning deferent techniques for observation and gap analysis [28].

3. COMPARATIVE ANALYSIS

A. *Dataset Description*

The study used ‘Extended Distress Analysis Interview Corpus (E-DAIC)’ dataset comparative analysis of ‘depression detection’. The ‘Extended Distress Analysis Interview Corpus (E-DAIC)’ dataset is collected from ICT California through Email communication. The dataset used to analysis and detection of multiple psychological distress conditions i.e. anxiety, PTSD (‘post-traumatic stress disorder’) and depression [27], [29]. The interviews are conducted for the dataset generation, there is a significant effort to generate virtual interviews. There are two subsets of the interview for the data generation. A first subset data generate through wizard-of-Oz (WoZ) agent and second subset of data generate AI- controlled agent i.e. Ellie [27]. The Dataset includes three parts ‘Data’, ‘labels’ and ‘E-DAIC Manual’. The first part ‘Data’ contain 4 visual features and 6 audio features and one patient id_Transcript.csv file. The second part labels are include training, development and test dataset and also additional part is ‘Detailed_PHQ8_Labels.csv’ contain a survey of 219 patents with their id_number, i.e. Patient Health Questionnaire (PHQ-8). E- DAIC Manual contain all information about dataset [27]. The Sessions with patients IDs ‘[300,492]’ in the range are collected with Human ‘WoZ-controlled agent and sessions with patients IDs ‘[600,718]’ are collected with an Ellie AI-controlled agent’ [27], [30].

B. *Comparative studies*

The comparative study of work concluding two methods: The first method is an ensemble hybrid model ensemble four machine learning the classifier and second method is the late fusion LSRG model also calculate the average prediction of the machine learning classifiers.

i) Ensemble Hybrid Model

The ensemble Hybrid model contain hybridization of the machine learning classifiers for generating hybrid model. The methodology of an ensemble hybrid model stated as follows.

- Methodology of Ensemble hybrid Model:

The methodological steps of an ensemble hybrid model are state in following algorithm 3.1.

Algorithm 3.1: *Depression Detection using Ensemble Hybrid model Algorithm*

This algorithm the state all steps involved for depression detection using an ensemble hybrid model as follows:

Start process of depression detection

Step 1: Initialization of process

→ Import all libraries ‘pandas’, ‘numpy’, ‘scikit-learn’, ‘matplotlib’, ‘seaborn’, ‘google collab’, ‘google.colab’.

Step 2: Data Loading and Preprocessing

→ Load dataset using pd.read_csv(), Drop not a required and target.

Step 3: Data Splitting for Training and Testing

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Define features (X) and target (y):

→ X = DataFrame without the label column.

y = label column.

Step 4: *Split the data into a train and test data sets*

→ Split the data into training and testing sets using ‘train_test_split()’ with 80%-20% split.

Step 5: *Model Initialization*

→ Initialize four different classifiers:

‘Logistic Regression’, ‘Support Vector Classifier’, ‘Random Forest Classifier’, ‘Gradient Boosting Classifier’.

Step 6: *Create an ensemble model using ‘VotingClassifier’ with soft voting:*

Combine the four classifiers into a single model.

Set voting='soft' to use predicted probabilities for the final decision.

Step 7: *Train the ensemble model on the training dataset.*

Step 8: *Model Evaluation*

→ ‘Accuracy Score’: ‘accuracy_score(y_test, y_pred)’.

‘Classification Report: classification_report(y_test, y_pred)’.

‘Mean Squared Error (MSE): mean_squared_error(y_test, y_pred)’.

Step 9: *Analysis of the Depression Levels*

→ 1. Count, the number of predictions for each label.
2. Calculate the probability of each label.
3. Compute the weighted average of labels to find the average depression level.
4. Find the closest individual depression level (0, 1, 2, or 3) to the calculated average.

Step10: Confusion Matrix and Visualization

→ 1. Generate a confusion matrix to evaluate model performance using 'confusion_matrix()'.
2. Visualize the confusion matrix using 'seaborn.heatmap()'.

The above an algorithm 3.1 implements an ensemble hybrid model. The ensemble model combined multiple classifiers (Logistic Regression, SVC, Random Forest, Gradient Boosting) and generate a single LSRG model to predict depression levels based on features of E-DAIC's dataset. The above algorithm 3.1 can apply on E-DAIC's Label and Detailed_PHQ8_label.csv dataset for depression detection and checking of performance with other machine learning and deep learning algorithms.

ii) Late fusion LSRG Model,

The Late fusion ensemble model contain average of prediction for the machine learning classifiers for generating the late fusion model. The methodology of an ensemble late fusion model stated as follows.

- Methodology of Ensemble the late fusion Model:

The methodological steps of an ensemble late fusion model are state in following algorithm 3.2.

Algorithm 3.2: *Depression Detection using Ensemble Late fusion method Algorithm*

This algorithm state all the steps involved for depression detection using an ensemble late fusion model as follows:

Start process of the depression detection

Step 1: *Initialization of the process*

→ Import all libraries 'pandas', 'numpy', 'scikit-learn', 'matplotlib', 'seaborn', 'google collab', 'google.colab'.

Step 2:	*Data Loading and Preprocessing*	
→		Load dataset using 'pd.read_csv()', Drop not the required and target.
Step 3:	*Data Splitting for Training and Testing*	
		Define features (X) and target (y):
→		X = 'DataFrame' without the label column.
		y = label column.
Step 4:	*Split the data into the train and test data sets*	
→		Split, the data into training and testing sets using 'train_test_split()' with 80%-20% split.
Step 5:	*Define and Train Individual Models*	
→		Initialize and train Logistic Regression, SVC, Random Forest, and Gradient Boosting models.
Step 6:	*Late Fusion (Voting Classifier)*	
→		Use Voting Classifier with soft voting to aggregate predictions from individual models.
Step 7:	*Train the ensemble model on the training dataset.*	
Step 8:	*The Model Evaluation*	
→		Evaluate Late Fusion model using metrics like Confusion Matrix, Accuracy, and Classification Report.
Step 9:	*Visualize Results*	
→		Visualize depression status distribution and confusion matrices.

The above an algorithm 3.2 implements an ensemble model of late fusion techniques. The ensemble model combine multiple classifiers (Logistic Regression, SVC, Random Forest, and Gradient Boosting) to predict depression levels based on PHQ-8 scores. In late fusion techniques a voting classifiers aggregate prediction from multiple classifiers for depression detection.

C. *Evaluation metrics*

The study proposed two algorithm for the comparative analysis, the first algorithm 3.1 proposed ensemble the hybrid model for the machine learning classifiers i.e. 'Logistic Regression', 'SVC', 'Random Forest', and 'Gradient Boosting'. Second algorithm 3.2 for the late fusion depressive prediction of the machine learning algorithm.

i) The evaluation metrics of Ensemble Hybrid model on E-DAIC's 'train_split.csv', 'dev_split.csv' and 'test_split.csv' contain 'accuracy score', 'classification report' and 'mean squared error'.

TABLE I: CLASSIFICATION REPORT 1

	Precision	recall	F1-score	Support
0	0.96	1.00	0.98	24
1	1.00	0.97	0.98	30
2	1.00	1.00	1.00	02
accuracy			0.98	56
macro avg	0.99	0.99	0.99	56
weighted avg	0.98	0.98	0.98	56

The Table I shows the classification report of an ensemble hybrid model on E-DAIC's 'train_split.csv, dev_split.csv and test_split.csv' dataset. Also the model gives 91.21% accuracy, 1.78% mean squared error, 1.78% mean absolute error and R2 score is 94.23.

ii) The evaluation metrics of an Ensemble Hybrid model on Detailed_PHQ8_label.csv contain 'accuracy score', 'classification report', 'mean squared error' and R^2 score is 99.46%.

TABLE II: CLASSIFICATION REPORT 2

	Precision	recall	F1-score	Support
0	1.00	1.00	1.00	43
1	1.00	1.00	1.00	103
2	0.98	1.00	0.99	44
3	1.00	0.97	0.98	29
accuracy			1.00	219
macro avg	0.99	0.99	0.99	219
weighted avg	1.00	1.00	1.00	219

The Table II shows the classification report of an ensemble hybrid model on Detailed_PHQ8_label.csv dataset. Also the model gives 99.54% accuracy, 0.45% mean squared error, 0.45% mean absolute error and R^2 score is 99.46%.

iii) The evaluation metrics of late fusion ensemble model on Detailed_PHQ8_label.csv contain accuracy score, the classification report and mean squared error.

The following Table III shows the classification report of late fusion ensemble model on Detailed_PHQ8_label.csv dataset. Also the model gives 99.54% accuracy, 0.45% mean squared error, 0.45% mean absolute error and R^2 score is 99.46%.

TABLE III: CLASSIFICATION REPORT 3

	Precision	recall	F1-score	Support
0	1.00	1.00	1.00	43
1	1.00	1.00	1.00	103

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2	0.98	1.00	0.99	44
3	1.00	0.97	0.98	29
accuracy			1.00	219
macro avg	0.99	0.99	0.99	219
weighted avg	1.00	1.00	1.00	219

4. RESULTS AND DISCUSSIONS

The results and discussion of comparison of the depression detection system includes performance of proposed work with existing algorithm of learning techniques. The proposed work contain ensemble (LSRG) Hybrid model using learning techniques and ensemble late (LSRG) fusion method.

A. *Performance Comparison*

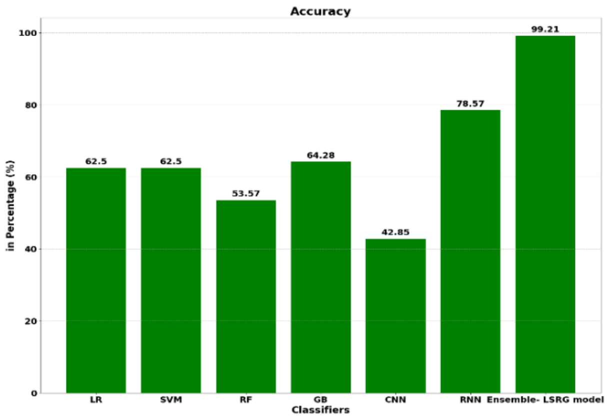

Fig. 1. Comparison of performance accuracy on 1st dataset

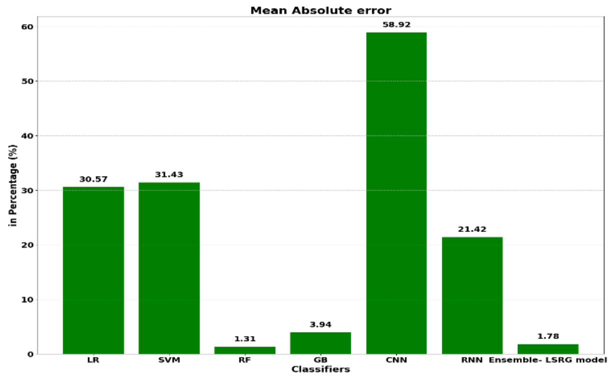

Fig. 2. Comparison of performance Mean Absolute error on 1st dataset

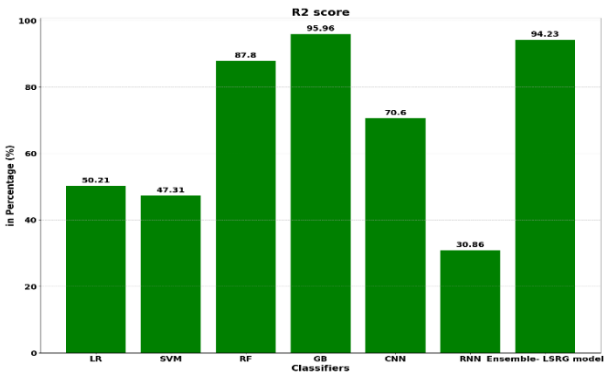

Fig. 3. Comparison of performance R2 score 1st dataset

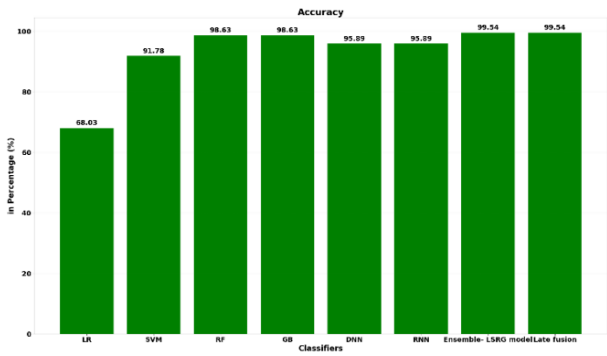

Fig. 4. Comparison of performance accuracy on 2nd dataset

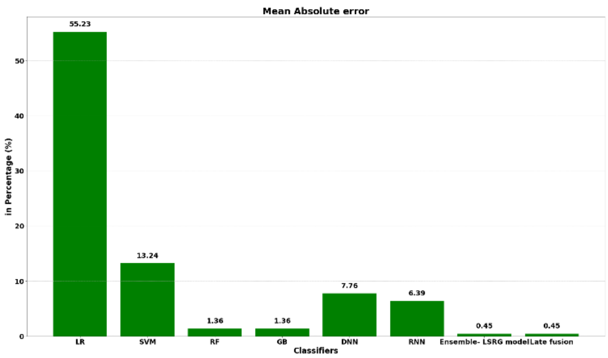

Fig. 5. Comparison of performance Mean Absolute error on 2nd dataset

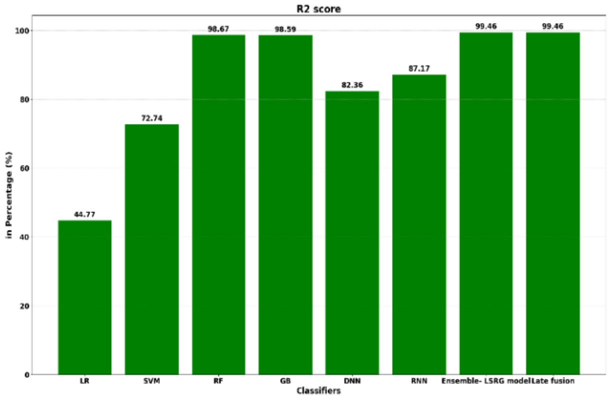

Fig. 6. Comparison of performance R^2 score 2nd dataset

The fig.1 shows the performance comparison of accuracy by using ensemble hybrid model (LSRG) with other existing learning techniques applied on E-DAIC's 'train_split.csv', 'dev_split.csv' and 'test_split.csv' dataset. The fig.2 shows the performance comparison of mean absolute error by using ensemble hybrid model (LSRG) with other existing learning techniques applied on E-DAIC's 'train_split.csv', 'dev_split.csv' and 'test_split.csv' dataset. The fig.3 shows the performance comparison of R^2 score by using ensemble hybrid model (LSRG) with other existing learning techniques applied on E-DAIC's 'train_split.csv', 'dev_split.csv' and 'test_split.csv' dataset.

The fig.4 shows the performance comparison of accuracy by using ensemble late fusion model with other existing learning techniques applied on Detailed_PHQ8_label.csv dataset. The fig.5 shows the performance comparison of mean absolute error by using ensemble late fusion model with other existing learning techniques applied on Detailed_PHQ8_label.csv dataset. The fig.6 shows the performance comparison of R^2 score by using ensemble late fusion model with other existing learning techniques applied on Detailed_PHQ8_label.csv dataset.

5. CONCLUSION AND FUTURE SCOPE

The comparative approach of depression detection based on the proposed learning algorithm compared with the existing algorithm. The study shows the various comparison parameters work on the two dataset. The first dataset is E-DAIC's 'train_split.csv', 'dev_split.csv' and 'test_split.csv' dataset and the second dataset is E-DAIC's Detailed_PHQ8_label.csv dataset. The first comparative parameter, i.e., accuracy on the first dataset using the ensemble hybrid model, gives 99.21% accuracy, which is higher than other existing algorithms, as shown in Fig. 1. The second comparative parameter, mean absolute error on the first dataset using the ensemble hybrid model, results in a mean absolute error of 1.78%, which is significantly lower than that of other existing algorithms, as shown in Fig. 2. The third comparative parameter, the R^2 score on the first dataset using the ensemble hybrid model, achieves a score of 94.23%, as shown in Fig. 3.

The study also work ensemble late (LSRG) fusion method. The first comparative parameter, accuracy on the second dataset using the ensemble hybrid model, achieves 99.54% accuracy, while the ensemble late (LSRG) fusion method gives 99.21% accuracy, both of which are higher than other existing algorithms, as shown in Fig. 4. The second comparative parameter, mean absolute error on the second dataset using the ensemble hybrid model, is 0.45%, and the ensemble late (LSRG) fusion method also results in 0.45% mean absolute error, which is significantly lower than that of other existing algorithms, as shown in Fig. 5. The third comparative parameter, the R^2 score on the second dataset using the ensemble hybrid model, reaches 99.46%, with the ensemble late (LSRG) fusion method also achieving a 99.46% R^2 score, as shown in Fig. 6. This study focuses on hybridizing learning algorithms to improve system performance. In future it try to implement for real time, Indian dataset also try to give good contribution to society and medical sector to monitoring patient 24*7 hours under observation.

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