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ENHANCED DETECTION OF STUDENT DEPRESSION USING AN OPTIMIZED MACHINE LEARNING MODEL

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ABSTRACT

Depression is an increasing concern among students adversely affecting academic performance and mental well-being. Early prediction is important for timely intervention. This paper aims to classify students into "Depressed" or "Not Depressed" categories utilizing the Depression Student Dataset. A comparative analysis of several traditional machine learning (ML) approaches, counting Gradient Boosting (GB), Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), XGBoost, LightGBM, AdaBoost (AB), Naïve Bayes (NB), and Decision Tree (DT) was performed to evaluate their predictive abilities. To enhance accuracy of prediction, this paper proposed an optimized LR model fine-tuned utilizing GridSearchCV. The optimized model shows superior performance with an accuracy rate of 98%, outstanding all other algorithms in this study. The findings highlight the efficiency of model tuning in improving depression classification results. This research proposed a robust framework for used ML to classify depression among students, contributing to early prediction and support strategies.

I. INTRODUCTION

Depression is a mental illness that can devastate mental stability, interfere with day-to-day functioning, and in certain situations, worsen into psychological trauma [1]. When psychological stress, anxiety, or depression is present, the human body issues a variation of chemicals, which causes a shift in nonverbal body language. These psychological conditions can be broadly categorized as depression, anxiety, or psychological stress, with anxiety being the initial stage and the most gradual [2]. Depression is the greatest severe phase of the psychological state, which may have a long-term detrimental effect on the individual's biological and cognitive health. It can arise from minor issues in daily routine. Stress is the second phase of the cognitive state, where the psychological state is concentrated due to the ongoing impact of anxiety [3]. Depression is a long-term disorder or disease mourned by most individuals. It is one of the most extraordinarily undertreated and underdiagnosed states of cognitive illness. It has stood to be a significant problem in the health, social, and economic sectors. It has also been a significant mortality problem and is slowly growing above the levels as the most significant disorder with zero to no treatment.

It is constantly connected to other underlying cognitive diseases and can induce the patient to trigger other latent cognitive diseases [4]. Due to the individual complexities and challenges of a studious life, Students are more likely to suffer from psychological anguish, which makes their cognitive health a significant global issue. Depression, which is a prevailing cognitive health condition among students, particularly degrades their social relations, educational attainments, and general well-being. It is essential to promptly and adequately identify these conditions to deliver timely intervention and assets. Approximately more than 260 million individuals universally suffer from depression disorder. Studies have shown that the prevalence of depression in students is higher than in the universal population with a range of 15% to 86% [5]. Determining whether someone is depressed can be done in a number of ways. The prediction of student depression has been done using traditional statistical approaches (TS).

Regression analysis has been employed in certain studies to observe the predictive value of a number of traits, counting social support, early life events, life events, parenting style, and stressful life events. Relationship studies have shown the significance of the association among traits like sadness, subjective social status, parenting style, social exclusion, and dark personality via calculating correlation coefficients. The organizational equation model enables a thorough examination of the difficult relations among a number of predicted traits counting psychological resilience, early trauma, coping mechanisms, perceived social support, gratitude, and parent-child attachment. This method helps students understand the indirect and direct ways of influencing depression.

There are some problems with employing TS approaches to forecast depression among students. First, TS approaches might not fully represent the complexity of depression because they presume linearity and independence among predicting factors. Furthermore, the number of forecasters must be in line with the taster size for conventional multivariate regression techniques. Thus, it is impossible to adequately assess the data and make use of any predictive features with this approach [6]. Also, obtaining a straightforward examination and consultation by a psychiatrist is the most reliable procedure, yet it is expensive and takes a long time. Multifarious self-administered psychometric tests for estimating depression are also commonly available.

Nevertheless, these tests are typically lengthy. The enormous number of questions prevents the taker from answering them with detailed answers, which can lead to incorrect estimation outcomes. The major disadvantage of these approaches is that the individual acknowledges that she or he is being experimented on for depression. This may induce damaging feelings in the issue and cause assessment refusal [7], [8]. To solve the problems found in traditional methods, we employ Artificial Intelligence (AI), including ML techniques, which have delivered developed analysis techniques for designing a depression prediction approaches. ML aims to develop approaches that can train to comprehend complicated patterns.

This advantage is useful in finding solutions to new problems, given past data and solution. Strategies are trained via ML and obtain regular-states and well-organized results. The promise of using ML methods in healthcare has shown to be feasible and remarkable due to their capacity to learn from huge amounts of heterogeneous data types and provide a valuable clinical insight. ML-based methods enable mental health practitioners to make prediction decisions and provide an effective understanding of cognitive problems. Through the development of insights from amorphous medical data, ML techniques aid in healthcare diagnosis and prediction. Patients with high-risk medical conditions can be identified and treated early thanks to the prediction results.

In order to help medical practitioners, anticipate the prognosis of depressive illnesses and support effective treatment outcomes, ML techniques enable arbitration among various behavioral features. Complex health data can be interpreted and visualized using these techniques. An influential theory on the prediction of depressive disorders can be developed thanks to visualization. The intricacy of depression is not adequately captured by the conventional clinical case identification approach. The design of the manifestation associated with depression disorder can efficiently be anticipated and detected by employing ML techniques. Consequently, the ML-based prediction approach is an efficient alternative for depression predictive investigation [9].

In this study, we proposed a hybrid method for predicting depressive illness. Gradient descent (GD) and LR were coupled to enhance the efficacy and performance of student depression prediction. To enhance the evaluation methods of cognitive health in pedagogical settings, this research will investigate how well measurement instruments using that hybrid model capture depressive illnesses. This effort to bridge the gap between advanced data driven procedures and traditional psychometric screening methods is considered in this study. It will also enhance students' overall mental well-being and the early identification of any cognitive health problems. The main contributions of our analysis are:

This study successfully reveals the pattern and rate of depressive illness in different student groups. In addition, a new scale for identifying student depression was developed. Hybrid ML models can better detect and screen for depressive illnesses in students. This is essential to implement timely and effective intervention, and to reduce the long-term deleterious effects of the disorders. Through the use of advanced data mining and psychological testing mechanisms, this research contributes to the academic literature. It creates as well a baseline for future research in the field of technology and cognitive care.

II. RELATED WORK

Recently researchers have presented studies on predicting student depression utilizing several ML techniques. The performance varied greatly depending on the technique and data utilized. In this section, we will present some of these studies. By [10] used ML models to forecast the risk characteristics associated with students' depression. The analysis instance consisted of 3984 students aged 15-10 years. The dataset was analyzed employing ML to forecast the risk characteristics associated with student cognitive health symptoms. The proposed utilized five ML techniques: ANN, RF, SVM, DT, and NB for prediction. The results demonstrated that the SVM technique had the highest accuracy of 92.5%.

According to [11] proposed a practical approach to predict student depression depending on ML techniques. Multiple ML techniques are employed, such as LR, RF, SVM, LDA, KNN, and NB. Based on performance analysis, the experimental outcomes reported that the RF model surpassed other techniques for the depression forecast by 89%. In turn [8] investigated models to forecast students' depression and reveal essential individual and family features. This investigation indicated individuals at threat of depression and recognized influential individual and family features in around 170 of data of families involved. The forecast accuracy of three ML techniques, SVM, Sparse Logistic Regression (SLR), and RF, were compared. The RF technique demonstrated the best accuracy of 86.27%.

By [12] proposed an effective study to forecast the student depression of an individual based on text input. The proposed model applied ML models, including LR, DT, RF, NN, KNN and a Hybrid Stacking (HS) model. The hybrid model utilized LDA as a feature selection process and integrated five ML classifiers. After comparing the performance of all ML approaches and the HS method. The HS model is achieving a better accuracy of 97%. According to. [6] proposed multiple ML models, such as KNN, LR, Non-linear SVM (N-SVM), and RF, to forecast differences in depression among students. The proposed approach utilized a dataset of 5,534 students and estimated personality characteristics. The results showed high performance in the forecast task, with the N-SVM achieving 95% accuracy.

In turn [13] proposed intelligent approaches for student depression prediction based on ML techniques. Three approaches were utilized to predict and categorize student depression in a dataset of 787 students via a number of phases, counting pre-processing, testing, and training. LR, KNN, and DT are the ML approaches applied in this work. With an accuracy rate of 77%, the results show the LR approach performed the best in terms of prediction. The study also revealed that male students are twice as likely to be obese compared to female students, that two out of five students suffer from mild depression, that 90% of students with depression do not seek treatment, and that male students generally have a higher BMI than their female counterparts.

By [14] proposed effective method to predict student depression utilizing multiple ML techniques including SVM, KNN, LR, DT, and NB. DASS21 was utilized to acquire data from 400 students. Various analysis matrices, like accuracy, precision, F1-score, and specificity were employed to compare the techniques. The finding results showed the KNN performed best, followed by LR. In turn [15] Utilized ML techniques to develop a student depression predictive approach. Multiple ML methods were applied in this proposed approach, including XGBoost, RF, DT, and LR, to detect persons who are more likely to have diagnosable depression. The collected dataset contained around 60,000 students and was partitioned into a 10:90 ratio for testing and training.

The proposed approach utilized cross-validation to improve model performance and investigated multiple evaluation measures such as Area Under Curve (AUC), sensitivity, and accuracy. Results indicated discriminative solid power in XGBoost, LR, and RF accuracy of 70%. According to [5] proposed an efficient approach for predicting student depression. The proposed approach uses a combination of ML algorithms with the General Health Questionnaire-12 (GHQ-12), a widely used tool for measuring psychological distress. First, with the help of a skilled psychiatrist, a full survey has been created for influential depression screening.

The questionnaire contains GHQ-12, job, sociodemographic, and career-related questions. Then, 16 various ML techniques were applied to investigate the dataset and determine predictors and trends of student depression in this demographic, including LR, NB, SVM, DT, Extremely Randomized Tree (ERT), RF, XGB, LGBM, CatBoost, KNN, GBM, AdaBoost, LDA, SGD, QDA, and ANN. Among the ML techniques, ERT has reached the highest accuracy of 90.26%.

III. RESEARCH METHOD

The research methodology of this work focuses on utilizing ML algorithms to classify students as either "Depressed" or "Not Depressed" based on the Depression Student Dataset. The objective is to evaluate how well these models predict depression. The workflow is shown in Figure 1, showing a step-by-step approach that contains dataset details, preprocessing steps, models, and evaluation metrics.

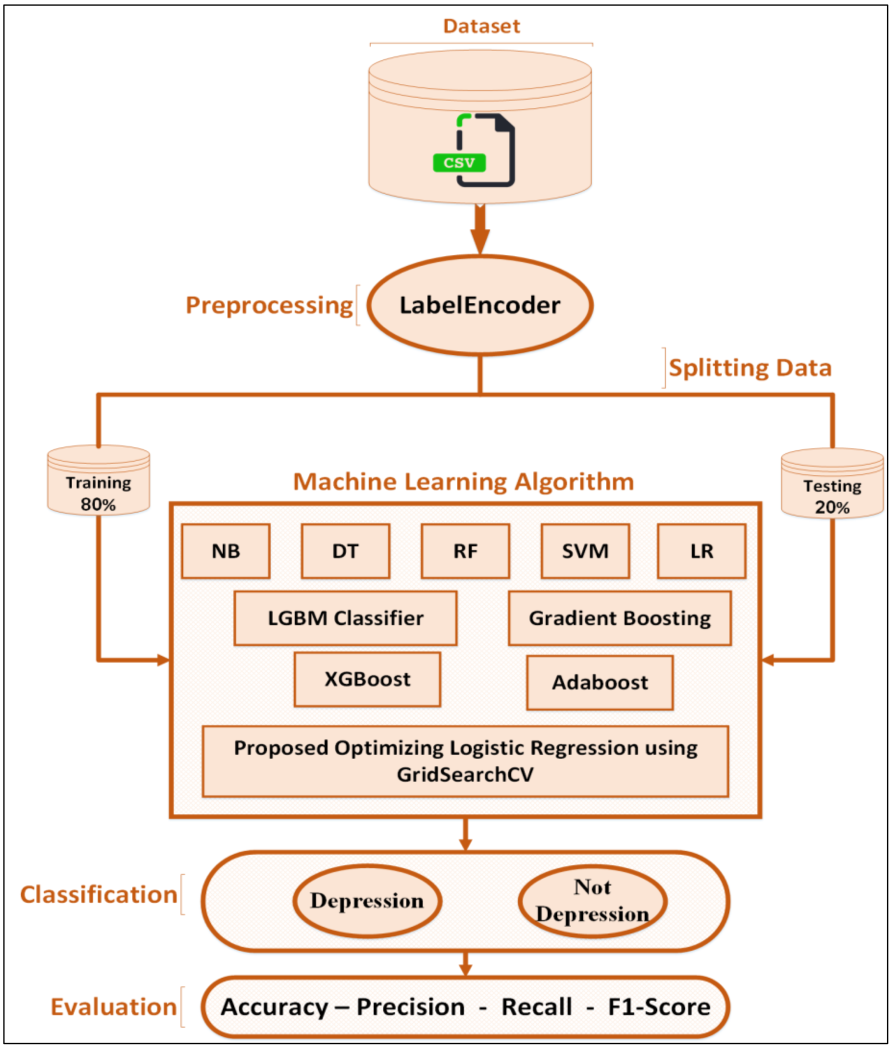

Figure 1: Workflow of the proposed depression detection model.
Source: Authors, (2026).

III.1 DATASET DETAILS

The Depression Student Dataset finds the connection between mental health and various other factors such as personal, academic, and lifestyle. Key attribution includes gender, age, financial stress, food practice, study hour, sleeping hours and academic pressure, satisfaction of study family history of psychiatric illness and symptoms of depression and suicidal thoughts. The dataset is also used for understanding the effects of factors such as sleep quality, diet and academic workload on mental well-being; applications include risk assessment for mental health, prevention strategies on various student populations. The dataset includes 502 samples with several attributes. The dataset of this study obtained from Kaggle that is available on the following link "Depression Student Dataset".

III.2 PREPROCESSING

Data preprocessing is an important step before applying ML algorithms, as it guarantees that the dataset is in a format that can be used to train models. The preprocessing methods used in this work are as follows:

III.2.1 Label Encoder

It was applied to convert non-numerical labels (such as "Male", "Female") into numerical values [16]. This is important for ML models that require numerical input. The encoding process ensures that individually unique label in a categorical feature is transformed into a corresponding numeric representation.

III.2.2 Splitting Dataset

The dataset was divided into training and testing parts, with 80% of the data utilized to training models and 20% for model performance testing.

III.3 MACHINE LEARNING ALGORITHMS

In this work various ML algorithms were chosen to evaluate performance in predicting depression. These models vary in their approach to classification, and their performance will be compared utilizing evaluation metrics. The following algorithms are utilized in this study:

III.3.1 Logistic Regression

LR is a ML algorithm utilized for binary classification problems, where the result variable has two possible classes, such as Depressed or Not Depressed. Modeling the likelihood that a given input point belongs to a specific class is the fundamental concept of LR [17], [18]. LR uses a logistic function (also known as the sigmoid function) to predict probabilities that are mapped between 0 and 1, as opposed to LR, which predicts continuous values. It is hence appropriate for categorization jobs.

LR determines the input features' weighted sum as shown in Equation (1):

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{1}$$

X are the input features, β are the weights, or coefficients, that the model learns throughout training.

The sigmoid function is utilized to transform the weighted sum Z's output into a probability as shown in Equation (2):

$$p = \frac{1}{1+e^{-z}} \tag{2}$$

The expected likelihood that the instance belongs to the positive class is represented by the result p.

III.3.2 Support Vector Machine

SVM is a supervised ML method that performs exceptionally well in classification tasks and it may also utilized for regression problems, [19]. Finding a hyperplane that best divides data points from several classes while optimizing the margin among them is the key objective of SVM [20]. The distance among the closest data points from individually class, also referred to as support vectors, and the hyperplane is known as this margin. The greater the margin, the more effectively the model can generalize to new data, hence minimizing overfitting [21].

When data is not linearly separable, SVM employs a technique known as the kernel trick. Even if the data is non-linearly separable in its original form, this method allows for the discovery of a linear decision boundary via transforming it into a higher-dimensional feature space. Because of this, SVM is very good at handling complicated and non-linear data. SVM does, however, face several difficulties. It can be computationally costly, particularly when using sophisticated kernel functions or huge datasets.

III.3.3 Random Forest

One popular ensemble ML technique for the regression and classification tasks is RF. With the help of bagging (Bootstrap Aggregating) it constructs a "forest" of DTs, each fitted with some part of the data. By averaging (for regression) or majority voting (for classification) the predictions of the ensemble trees, we obtain the final prediction. RF decrease overfitting because of the randomness on both data subsets and feature selection by enhancing model generalization [22]. It supports missing values, does not need feature scaling, and presents you with feature importances. In contrast, although RF achieves high accuracy and is fairly robust, it sometimes encounters excessive computation time and prediction becomes slow with many trees or large datasets. Despite these limitations, RF is still widely used as it is a versatile, easy to use ML technique that performs well in a variety of tasks.

III.3.4 Gradient Boosting

GB is an ensemble ML technique utilized for classification and regression tasks. Models are created one after the other, with separately new model fixing the mistakes of the ones that came before it [23]. In order to generate a powerful prediction model, it integrates weak learners, usually DT. GB uses gradient decent to train trees to reduce residual errors from the prior model, in contrast to RF which creates trees independently. Based on the gradient of the error function, this procedure iteratively modifies the model. Although GB excels at handling complicated datasets and yields high accuracy, its computational cost and hyperparameter sensitivity necessitate careful adjustment for best results.

III.3.5 Extreme Gradient Boosting

XGBoost, the gradient boosting version for regression and classification problems [24], is a refined and scalable implementation of GB. It is an extended version of classic GB by improving speed, accuracy and trying to avoid overfitting. Similar to other methods such as AdaBoost, XGBoost works in a consecutive manner and each tree that we build tries to correct the errors made by the previous trees. It adopts DT as the base learners, and focuses on minimizing a loss function by using a greedy procedure. XGBoost stands out for regularization (L1 and L2) to avoid overfitting, which makes it noisy and effective. It also includes tree pruning, column and row subsampling for improved generalization, and parallelization to speed up computation. Moreover, XGBoost has hyperparameters such as tree depth, learning rate and the number of trees to fit performance that have made it in favor of many ML competitions and industrial application.

III.3.6 Light Gradient Boosting Machine

LightGBM is efficient and scalable GB framework developed via Microsoft, designed for fast training and handling large data sets [25]. It is particularly favored for classification tasks due to its speed, accuracy, and low memory consumption. Like other GB methods, LightGBM builds an ensemble of DT sequentially, individually tree fixing the mistakes of the one before it. What sets LightGBM apart is its use of histogram-based learning, where feature values are grouped into discrete bins instead of evaluating all possible split points, which reduces computation time and memory usage, making it highly efficient for large datasets.

III.3.7 Decision Tree

For classification and regression tasks, its powerful supervised ML approach, DT is applied. Each node in the internal nodes of the tree image stands for an attribute, each branch represents a decision rule, and each leaf node corresponds to an outcome. This tree-like structure is formed by repeatedly splitting the data based on feature values [26]. To maximise class separation, or to minimize the error in prediction along all splits (not just at leaf nodes), the "best" split points are determined using Gini impurity, Entropy (for classification), or Mean Squared Error (for regression). Simple Make: (a) Decision trees have the risk of overfitting and deep decision trees in our setting are often DTs, although they are intuitive to comprehend and visualize. Ensemble/Bagging techniques like RF, GB or pruning can mitigate it. It -- and also like OVR which more we will discuss later -- tend to over-fit, but is flexible for both numerical as well categorical input.

III.3.8 Naive Bayes

NB is efficient probabilistic classifier that is frequently utilized for classification tasks, especially in text classification applications like sentiment analysis and spam detection. It allocates the class with the highest posterior probability after estimating the likelihood of class labels given a collection of features [27]. NB is regarded as "naive" as, given the class title, it presumes that the properties are unrelated to one another, which is often unrealistic but still works well in many situations, especially when feature independence is approximately true. Despite this assumption, NB can perform surprisingly well in practice, particularly in large datasets. Variants of NB, such as Multinomial NB for discrete data and Gaussian NB for continuous data, are utilized based on the type of data. Although its simplicity and assumptions may limit its performance in more complex datasets, NB remains a fast, scalable, and robust algorithm, widely utilized for text classification, spam filtering, medical diagnostics, and recommendation systems.

III.3.9 Adaptive Boosting

AB is a classification ensemble learning strategy that builds a strong classifier via combination some weak classifiers [28]. It trains a sequence of weak models, frequently decision stumps, with each model concentrating on fixing the mistakes of the one before it. After each model is trained, the weights of the misclassified instances are raised, giving harder cases more weight than the initial equal weights assigned to all training examples. The overall prediction is then obtained by combining the output of all weak classifiers and stronger classifiers contribute more to a more accurate final classifier.

AB improves the accuracy and mitigates over-fitting over individual classifiers, however AB can be sensitive to noisy data points and outliers because more weight is given to misclassified examples, which could magnify the noise from the mislabeled cases. Nevertheless, AB is a popular method because it is simple and does work well at boosting the performance of weak classifiers.

III.4 PROPOSED OPTIMIZING LOGISTIC REGRESSION USING GRIDSEARCHCV

This paper proposed an optimized LR model utilizing GridSearchCV, a technique that finds the ideal hyperparameters for the model via doing an exhaustive search throughout a given parameter grid. By methodically experimenting with different hyperparameter combinations, this methodology enhances the model's performance. For the LR model, we focus on tuning key parameters such as C (regularization strength), solver (optimization algorithm), and penalty (regularization technique). The parameter grid includes values for C ranging from 0.01 to 100, solvers 'liblinear' and 'lbfgs', and the 'l2' penalty.

The grid search is performed with 5-fold cross-validation to ensure robust evaluation of the model, with the goal of maximizing accuracy in classifying students as "Depressed" or "Not Depressed." The search is conducted by fitting the model with the training data and evaluating all parameter combinations, with the best hyperparameters selected based on their performance. After completing the grid search, the optimal hyperparameters are retrieved utilizing grid.best_params_, which fine-tunes the LR model for improved predictive performance.

III.5 EVALUATION METRICS

The performance of each ML model will be evaluated utilizing the following metrics [20]:

- Accuracy: The ratio of accurate forecasts (including true positives and true negatives) to all occurrences, which can be calculated by Equation (3).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TN} + \text{FN} + \text{TP} + \text{FP}} \tag{3}$$

- Precision: shows how many of the anticipated depressed students were actually depressed is indicated via the ratio of genuine positive predictions to all predicted positives, which can be calculated by Equation (4).

$$\text{precision} = \frac{\text{TP}}{\text{FP} + \text{TP}} \tag{4}$$

- Recall: The ratio of actual positives to true positive forecasts, which indicates the number of students who were accurately diagnosed as truly depressed, which can be calculated by Equation (5).

$$\text{Recall} = \frac{\text{TP}}{\text{FN} + \text{TP}} \tag{5}$$

- F1 Score: A balanced indicator of a model's capacity to accurately categorize both positive and negative cases is the harmonic mean of precision and recall, which can be calculated by Equation (6).

$$F - measure = \frac{2 \times (Recall \ * Precision)}{Recall + Precision} \tag{6}$$

These evaluation metrics will be calculated for each model to assess which ML algorithm provides the best predictive performance for identifying depression in students.

IV. RESULTS AND DISCUSSIONS

In this study many ML models were evaluated for their ability to classify depression in students, with the performance measured by accuracy as shown in Figure 2. The results of proposed model are summarized in Table 1. Our proposed method was the most accurate among the models compared, indicating the highest capability to detect depression among students. LR (97%), SVM (97%), and NB (97%) followed closely with strong results, demonstrating that simpler models can still perform very well in this classification task.

On the other hand, DT Classifier was very weak with accuracy of 81%, it indicates that the model tend to overfit, especially with depression data set is complex. As RF, GB, XGBoost and AB all reached 94%, but did not perform much better than the simpler models in this case. The better performance of proposed methods indicates that the applied algorithm – probably a specific combination of best features and hyperparameters – can extract the complex structure of dataset better than the rest. The results indicate that although traditional classifiers can achieve good accuracy, advanced models such as the proposed one would deliver a substantial advantage in performance, and be an effective method to address this category of classification challenge.

Table 1: Comparative Performance of Various ML Models and the Proposed Model.

Model	Precision	Recall	F1-score	Accuracy
LR	97%	97%	97%	97%
SVM	97%	97%	97%	97%
RF	95%	94%	94%	94%
GB	94%	94%	94%	94%
Xgboost	94%	94%	94%	94%
LGBM Classifier	96%	96%	96%	96%
DT	81%	81%	81%	81%
NB	97%	97%	97%	97%
Ada Boost	95%	94%	94%	94%
Proposed	98%	98%	98%	98%

Source: Authors, (2026).

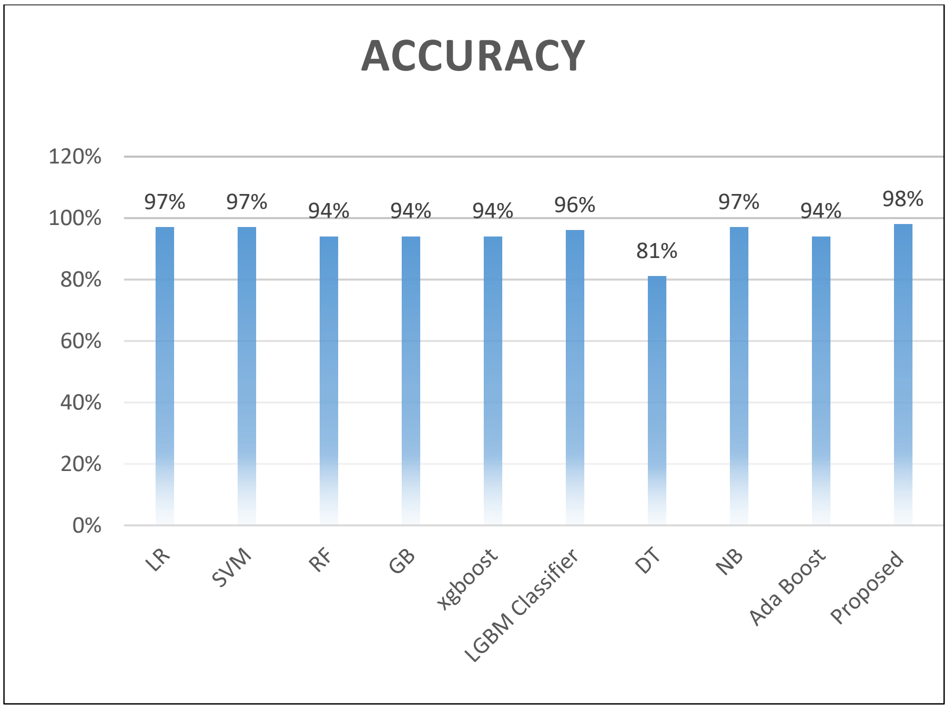

Figure 2: Model accuracy comparison.
Source: Authors, (2026).

The results obtained from different ML approaches for the prediction of the target variable are summarized in Table 2. The models of the state-of-the-art studies compared with optimized LR utilizing GridSearchCV, which is the proposed model in this study. The previous studies employed a range of algorithms, and the results varied significantly among models. For example, Qasrawi et al. [10] utilized multiple algorithms, counting DT, RF, ANN, and NB, and achieved a high accuracy of 92.6% utilizing SVM. While, Nayan et al. [11] explored a variety of models like LR, RF, LDA, KNN, and NB, with SVM once again yielding the highest accuracy at 91.49%. These results reinforce the strength of SVM in this context, as it outperforms many other traditional classifiers. Gil et al. [8] found that RF achieved the highest accuracy (86.27%) in their study, while Rahman et al. [12] was got an high 97% accuracy utilizing a hybrid stacking model. This hybrid model, which combined multiple algorithms, clearly benefited from the synergistic effect of the different classifiers. The hybrid approach suggests that stacking can lead to superior performance by leveraging the complementary strengths of various models, especially when no single model dominates across all metrics. While Hu et al. [6] utilized multiple models that counting RF and K-NN, but found that N-SVM (a variant of SVM) achieved the highest accuracy of 95.2%.

Villanueva et al. [13] utilized KNN and DT, but their RF model produced the high accuracy, although lower than many of the other models (77%), demonstrating that RF may not always perform optimally across all datasets. Zhai et al. [14] experimented with a combination of models, including DT, XGBoost, LR, and RF, but found that all models achieved an accuracy of only 70%. This suggests that while these models can be useful, further tuning or a different feature set might be necessary to improve performance. Mumenin et al [5] tested a broad range of algorithms, including LR, NB, SVM, DT, and ensemble methods like ERT, RF, XGB, LGBM, and KNN, with ERT (Extremely Randomized Trees) yielding the highest accuracy of 90.26%. This broad comparison underscores the complexity and variability of model performance, as different datasets may favor different algorithms. The proposed model of this work via LR through GridSearchCV achieved a high accuracy of 98%. This result is important because LR, although a simpler model compared to others like RF or Hybrid Stacking, shows competitive performance once hyperparameters were tuned utilizing GridSearchCV. The accuracy of 98% is very close to the best results stated in the literature. This suggests that with careful optimization, even simpler models can perform at the level of more complex algorithms.

Table 2. A comparison of the proposed model with state-of-the-art studies.

Reference	Year	Techniques	Accuracy %
Qasrawi et al. [10]	2022	DT	88.5
		SVM	92.6
		RF	92.4
		ANN	91.9
		NB	87.1
Nayan et al. [11]	2022	LR	78.07
		RF	91.3
		SVM	91.49
		LDA	79.58
		KNN	91.3
		NB	73.53
Gil et al. [8]	2022	SLR	78.43
		SVM	80.39
		RF	86.27
Rahman et al. [12]	2023	LR	85
		DT	92
		RF	96
		NN	96
		KNN	96
		hybrid stacking model	97
Hu et al. [6]	2024	N-SVM	95.2
		RF	90.4
		K-NN	92.26
Villanueva et al. [13]	2024	RF	77
		KNN	70
		DT	62
Zhai et al. [14]	2024	XGBoost	70
		LR	70
		DT	66
		RF	70
Mumenin et al. [5]	2024	LR	77.95
		NB	75.38
		SVM	86.15
		DT	71.28
		ERT	90.26
		RF	86.15
		XGB	84.10
		LGBM	84.62
		CB	82.56
		KNN	74.87
		GBM	84.10
		AB	80
		QDA	81.54
		LDA	84.62
		SGD	83.59
		ANN	86.15
Proposed model	2025	Proposed Optimizing LR using GridSearchCV	98

Source: Authors, (2026).

This study Proposed Optimizing LR Model shows high performance, outperforming many traditional ML techniques and even hybrid models, further proving the importance of optimization in improving predictive accuracy in depression classification tasks.

V. CONCLUSIONS

This work proposed optimized LR models and GridSearchCV for hyperparameter tuning classification problem. Very excellent accuracy of 98% has been achieved in the proposed approach and this is highly competitive compared with other state-of-the-arts ML techniques often employed for these monitoring tasks. This finding indicates that, with the right optimization, even those simpler models such as LR may achieve better performance than more-complicated methods including accuracy, interpretability and computational efficiency. The results indicate that well-calibrated traditional models such as LR can be just as effective as more complex approaches, providing a practical and resource-efficient solution. For future work, other feature selection techniques may be examined so that they can apply or ensemble the LR model and could improve the accuracy.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Saad Adnan Abed, Mohammed Salah Ibrahim, Omar Hammad Jasim, Ahmed Adil Nafea.
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Approval of the final text: Saad Adnan Abed, Mohammed Salah Ibrahim, Omar Hammad Jasim, Ahmed Adil Nafea.

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