



Predicting Student Depression using Machine Learning: A Comparative Analysis of Machine Learning Algorithms for Early Depression Detection in Students

Abdimalik Osman Hassan
*ICT Department,
MyBank LTD
Mogadishu, Somalia*
abdimalik.osman@mybank.so

Ismail Mohamed Jamal
*Jamhuriya University of
Science and Technology
Mogadishu, Somalia*
ismail@just.edu.so

Shuab Daud Ahmed
*Jamhuriya University of
Science and Technology
Mogadishu, Somalia*
shuabaud@just.edu.so

Abdifatah Ugas Abdullahi
*Jamhuriya University of
Science and Technology
Mogadishu, Somalia*
ugas@just.edu.so

Abstract— Depression among students is emerging as a problem that seriously impairs their academic performance, personal life, and future career prospects. The authors apply machine learning to predict possibilities for depression among students with consideration of a number of personal, academic, and lifestyle variables. Different model types were tried, including logistic regression, random forest, and support vector machine. The performances of all these were checked; among all these, logistic regression yielded the best results with 85% accuracy, and all precision, recall, and F1-score values were also pretty well-balanced. Class imbalance was addressed using SMOTE to improve sensitivity for the model on underrepresented classes. Some of the actionable points to come out of this were focused counseling and support programs by mental health organizations within educational institutions. It also illustrated the use of machine learning, which makes the handling proactive as far as mental health challenges are concerned and opens wider vistas for applications both in the educational and healthcare fields.

Index Terms – Depression Prediction, Machine Learning Models, Logistic Regression, Random Forest, Support Vector Machine (SVM), SMOTE (Synthetic Minority Oversampling Technique, Academic Stress, Financial Stress.

I. INTRODUCTION

Depression among students has become a major public health concern that influences academic achievements, interpersonal relationships, and overall life. The prevalence of factors such as academic stress, financial problems, and lifestyle behaviors is highly related to mental health disorders among university students, which was disclosed by numerous studies [1]. Further, the COVID-19 pandemic made things worse with disrupted daily life routines, increased isolation feelings, and amplified anxiety-all joining hands to exacerbate the global rise in mental health issues [2]. The effects of depression among students, if not treated, encompass not only poor academic performances but also higher dropout rates,

reduced employability, and ideation in extreme cases of the disorder [3]. Recent developments in ML provide a befitting avenue towards the mental health crisis by allowing early detection and intervention. ML algorithms are very good at analyzing complex, high-dimensional data sets, and hence represent an ideal candidate for discovering patterns associated with mental health disorders [4]. It proved that ML might detect stress and depression using a wide range of data, from physiological signals to survey responses, social media activities, and behavioral measures [5]. For example, some supervised models like SVM, RF, and Logistic Regression have been applied in the classification of states of mental health with high accuracy [6]. The models, apart from improving the capability for detection, also provide insight into the root cause of challenges in mental health [7].

This study predicts students' depression using machine learning techniques informed by psychological, academic, and lifestyle variables. The aim is to develop a predictive framework that will highlight students in the risk group, enabling early interventions with personalized support. This research study will bridge the gaps in the present mental health monitoring systems by integrating various data sources and using advanced ML algorithms. This may also lead to further information on policy decisions and intervention strategies within educational institutions and mental health services [8].

To this end, the research explores techniques such as ensemble learning and feature importance analysis to identify the variables that serve as the best predictors of depression. It is also hoped that the findings will support educators, counselors, and policy makers in the provision of effective support mechanisms for ensuring timely help for students who need it most.

II. RELATED WORK

The rising trend of depression and its negative effects on the overall well-being and academic performance of

students has attracted considerable attention. Numerous research studies have explored the different aspects of depression, its causes, and the suitability of machine learning approaches for early detection and intervention.

A study conducted among high school students of Karachi revealed that the prevalence of anxiety and depression is 53.25% and stated family history and socio-economic factors as major contributors to mental disorders in adolescents [9]. In another study, academic stress, social anxiety, and disruption in lifestyle were identified as significant contributing factors to depression among college students [10]. It is clear that several psychosocial and environmental factors must be considered when analyzing students' mental health.

Machine learning has increasingly been accepted to predict and identify depression. Random Forest along with data balancing methodologies such as SMOTE and Tomek links was utilized to overcome data imbalance challenges in depression prediction datasets with accuracy 94.17%, demonstrating that hybrid sampling methodologies perform far better to enhance the performance of prediction models on mental health datasets [11]. Symptoms of depression were even identified with accuracy 85.7% by passive sensing strategies. This was conducted through mobile devices and wearable sensors that gathered information on behavioral characteristics, indicating the potential of longitudinal data for early intervention [12]. The predictive quality of depression was then examined from both psychological and academic fronts, where general and academic anxieties were indicated as major predictors of depression in university students. It has been suggested that interventions aimed at controlling these anxieties would decrease the onset of depressive symptoms [13]. Furthermore, the relationship among alexithymia, anxiety, and depression in relation to self-efficacy in academic students was investigated, highlighting the interaction between emotional control and academic performance [14]. Passive sensing is emerging as a useful methodology in measuring depression dynamics.

Features from wearable device and mobile phone-based sensor data have been shown to be effective in facilitating week-level monitoring and forecasting of depressive symptoms with recall rates of up to 81.5%. These findings highlight the importance of involving symptom features, such as changes in sleeping patterns and loss of activities as specified by the DSM-5, thus providing comprehensive information on depression among university students [15].

These studies put into perspective a nexus where psychosocial, academic, and technological insights are harmoniously used in devising comprehensive strategies for the detection and intervention of depression among students.

III. GAP ANALYSIS

Student depression stands as a vital educational issue which affects both student academic achievement and their relationships with peers and emotional health. The disorder results from three main factors: academic pressure together with financial problems and social fear. Additional studies need to explore the complex interrelations between these factors across various socio-cultural settings and institutional environments. The available datasets do not contain student-specific challenges from particular regions which causes generalized models to produce inaccurate results for local conditions.

Machine learning (ML) methods demonstrate effectiveness in identifying depression. Most approaches experience difficulties with unbalanced data especially severe cases which results in reduced accuracy together with inadequate representation of important instances in predictive models. The systematic review shows that supervised ML techniques predominate mental health applications but training data restrictions regarding class balance and demographic representation create obstacles to model generalizability and fairness [16].

The detection of early depression symptoms remains a significant problem to solve. Longitudinal studies have attempted to monitor depression development yet most research focuses on predictive model development for anticipating depressive symptoms before their onset. Mobile applications and wearable devices operate as passive sensing technologies that demonstrate potential for making early detections. Research has not fully explored these technologies because existing studies investigate only sleep patterns and phone usage without studying essential behavioral indicators. Research demonstrates that using various passive sensing data sources including physical activity and sleep quality and social interactions allows the identification of depressive symptoms thus validating their broader implementation [17].

The majority of ML research concentrates on predictive accuracy without examining output interpretability which is vital for developing actionable interventions. The lack of interpretability in research findings prevents their practical application for educational staff and mental health professionals. The study demonstrates the need to employ explainable AI methods that enhance both the clear understanding and practical implementation of depression detection models in educational settings [18].

The creation of predictive frameworks needs multiple predictor integration and data imbalance solutions together with early intervention capabilities. The research addresses these gaps through contextual dataset enrichment with advanced passive sensing features which enhances the actionability and interpretability of student mental health improvement insights.

IV. METHODOLOGY

The study applies machine learning to the prediction of student depression and will consider comprehensive preprocessing and feature engineering, with their evaluation, to make sure derived insights are appropriate and useful.

A. Dataset Description

For academic, personal, and lifestyle variables in students, there are 27,901 records in total in this dataset. These included:

- Demographic Information: gender, age, city
- Psychological Factors: Academic pressure, financial stress, sleep duration, suicidal thoughts.
- Academic Metrics: Satisfaction in studies, CGPA, job satisfaction.
- Lifestyle Attributes: Dieting habits, work/study time, and family medical history of insanity.

The dataset was retrieved from verified repositories to ensure its reliability. Target variable is binary with values as below:

- ✓ 1: Depressed
- ✓ 0: Not Depressed

The data showed an imbalanced class distribution of 58.5% of the samples in the class "Depressed" and 41.5% in the class "Not Depressed".

B. Data Preprocessing

Handling Missing Values:

Missing numerical values were replaced by the median to ensure the data are robust against outliers. The imputation of the categorical values was done with the most frequent category to maintain the integrity of the data.

Outlier Detection and Removal:

Outliers of continuous variables, which were Financial Stress and Work/Study Hours, were removed by using the IQR method in order to improve data quality.

Feature Scaling:

Numerical features will be standardized by the Standard-Scaler, which then puts all these features on similar scales for much better performance within the models.

Encoding Categorical Variables:

Categorical variables included: Gender and Dietary Habits One-hot encoding these features would allow them to become presentable by a machine learning

model. The Ordinal variables that are available require consideration of their already pre-existing order via ordinal encoding.

Handling Imbalanced Classes:

To reduce the impact of imbalanced classes, SMOTE was used to generate synthetic samples for the minority class.

C. Feature Engineering

Feature Creation:

Interaction terms, such as Academic Pressure and Financial Stress, have been created in order to understand the combined effects of important predictors on depression.

Feature Transformation:

Features such as Academic Pressure and Financial Stress, which are numeric and show skewed distributions, have been log-transformed.

Feature Selection:

SelectKBest along with the f_{classif} statistical test has been used to select the top 10 predictors of depression:

- Sleep - less than 5 hrs, more than 8 hrs
- Unhealthy eating
- Academic pressure
- Financial stress
- Dissatisfaction with studies
- Age
- Suicidal tendencies.

D. Machine Learning Models

The following models have been trained and tested to come up with the best approach to predict student depression:

Logistic Regression (LR): Chosen for simplicity, interpretability; after tuning, 85% with balanced precision and recall

Random Forest (RF): Leverage because of non-linear relationship capturing feature importance analysis; it is at 84% with a strong recall.

Support Vector Machine (SVM): A kernel-based classification method. After hyper-parameter tuning, the best accuracy can get to 84%, with the best recall.

Decision Tree (DT): Interpretability was desired, but this model was slightly overfitting; it had an accuracy of 82%.

K-Nearest Neighbours (KNN): Having a balanced recall, though slightly lower in precision gave an accuracy of 82%.

E. Model Training and Evaluation

A stratified sampling technique was adopted to split the data into 80% for training and 20% for testing.

Following is one of the important metrics to have been considered while understanding the working of this model:

Accuracy: Overall correctness in predicting.

Precision: The ratio of accurate positive forecasts.

Recall: Sensitivity in identifying students with depression.

F1-score: Ideal equilibrium between Precision and Recall

Confusion Matrix: Visualization of Classification Performance.

F. Hyperparameter Turning

The model's parameters have been optimized by grid search employing 5-fold cross-validation. For Example:

In Logistic Regression, Inverse of regularization strength

C and Solver has been optimized.

In Random Forest, No. of Trees, and max depth tuned.

SVM: Type of kernel and strength of regularization have been tuned.

Implementation and Tools:

The system was implemented in Python libraries:

- *Data Preprocessing:* pandas, NumPy, scikit-learn.
- *Visualization:* seaborn, matplotlib.
- *Modelling:* scikit-learn, imbalanced-learn.

Best Model Selection:

Logistic Regression was selected as the best since it:

Balanced performance across metrics Is simple to scale.

Provides high interpretability, very helpful for decision-making by stakeholders.

Statistical Measures:

Statistical measures were used:

Accuracy: Proportion of correct predictions.

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

Precision: Proposition of True Positives among predicted Positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: Proportion of actual positives correctly predicted.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: Harmonic mean of precision and recall.

$$\text{Precision} = \frac{TP}{TP + FP}$$

The F1 Score is the harmonic mean of precision and recall; hence it gives a balanced measure of a model's classification performance. It depicts how well the methods work in a balance between the percentage of correctly identified positive instances and the proportion of real positives. The F1 Score informs about a method's capability to deliver appropriate and reliable classification results. According to the literature, the F1 Score harmoniously unites precision and recall in one single score that expresses methodological strengths and classification accuracy.

V. RESULTS AND DISCUSSION

The various machine learning models that will be considered for performance evaluation classify depression among students for the project Predicting Student Depression Using Machine Learning. This section covers aspects related to performance metrics, insight from the models, and practical implications:

A. Model Performance

Several models were trained and tested in regard to accuracy, precision, recall, and F1-score toward the best model approach in predicting depression among students. The result is summarized below.:

Best Model (Logistic Regression): The Logistic Regression exhibited an accuracy of 85%, while precision, recall, and F1-score were 86%, 88%, and 87%, respectively. It has a good balance in all the metrics and is computationally simple; hence, the best for this task.

Feature Scaling:

Numerical features will be standardized by the Standard- Scaler, which then puts all these features on similar scales for much better performance within the models.

Encoding Categorical Variables:

Categorical variables included: Gender and Dietary Habits One-hot encoding these features would allow them to become presentable by a machine learning model. The Ordinal variables that are available require consideration of their already pre-existing order via ordinal encoding.

Handling Imbalanced Classes:

To reduce the impact of imbalanced classes, SMOTE was used to generate synthetic samples for the minority class.

Random Forest: Also, the model Random Forest fared comparatively better with an accuracy of 84%, Precision-

85%, Recall-88%, and an F1-score of 87%, whereas that by Logistic Regression. Its good performance was likely because it captures the non-linear relationship, albeit more computationally costly.

Support Vector Machine: The SVM model achieved an accuracy of 84%, precision of 85%, a recall of 88%, and an F1-score of 87%. The performance metrics from the SVM, though good on paper, indicated that before preprocessing with SMOTE, class balance was an issue.

Decision Tree: *Decision Tree-82% accuracy, 84% precision, 86% recall, and 85% F1-score. This model is overfitting a lot to the training set since it's quite deep and sensitive to noise.

K-Nearest Neighbours: *The best performances obtained with KNN were 82% accuracy, 82% precision, 88% recall, and 85% F1-score. Although KNN provides balanced recall, the lower precision provided by this model is indicative of susceptibility to false positives.

B. Lessons Learnt from Model Evaluation

a. Logistic Regression Strengths:

- Consistent performance on all metrics.
- Interpretable coefficients; this helped in knowing the important predictors like academic pressure and financial stress.

Random Forest Insights:

- Provided feature importance rankings, thus confirming predictors like Sleep Duration, Financial Stress, and Academic Pressure.
- It needs tuning to avoid overfitting and find the best tree depth.

SVM Challenges and Strengths:

- Initially problematic with class imbalance but performed impressively after applying SMOTE.
- Does well in high-dimensional space but is computation- ally expensive.

b. Overcoming Overfitting in Decision Tree:

Overfitting would be overcome through pruning, limiting max-depth, and cross-validation.

Limitations of KNN:

While ease of implementation may be the positive attribute of KNN, the lesser precision of KNN suggests that it fails to differentiate between values with close features in the case of an imbalanced dataset.

C. Practical Consequences

This therefore becomes highly valued by educational institutes and mental health professionals alike.

Actionable Insights:

The top models go further to establish the most important predictors of depression, which are: Academic Pressure, Financial Stress, Duration of Sleep, and Suicidal Thoughts.

These could be useful in informing the implementation of mental health interventions; for example, selective counseling or stress management programs.

The chart provided (Figure 1) compares the performances of different machine learning algorithms, namely Logistic Regression, Random Forest, Support Vector Machine, K-Nearest Neighbours, and the Decision Tree with respect to their performances based on Accuracy and F1-score. Among them, Logistic Regression is well-balanced; hence, it is relatively accurate in making its predictions with consistency in both positive and negative classifications. Random Forest and SVM give closely comparable results, reflecting a good robustness for complex datasets. KNN and Decision Tree also provide acceptable accuracy, but their F1-scores are relatively lower-perhaps due to the problem of false positives and overfitting, respectively. Overall, Logistic Regression and Random Forest turn out to be the most reliable models for the prediction of depression.

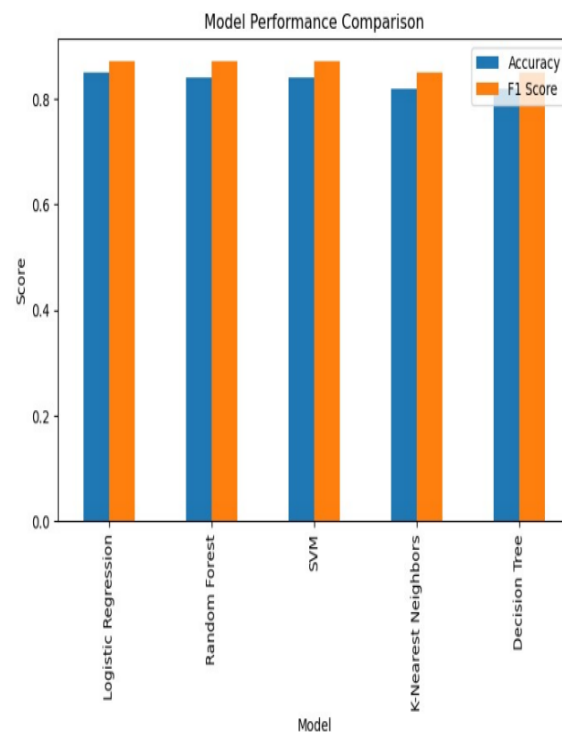


Figure 1 Model Comparisons

D. Discussion of Results

Comparing Models: Logistic Regression, Random Forest, and SVM are performing comparably well since their high recall can identify the majority of depressed

students correctly. Similarities in the performances indicate strengths of these models in terms of handling high-dimensional and imbalanced data.

TABLE I COMPARISON OF DIFFERENT PERFORMANCE ALGORITHMS

| Models | Accuracy | Precision | Recall | F1-Score |
|------------------------|----------|-----------|--------|----------|
| Logistic Regression | 85% | 86% | 88% | 87% |
| Random Forest | 84% | 85% | 88% | 87% |
| Support Vector Machine | 84% | 85% | 88% | 87% |
| Decision Tree | 82% | 84% | 86% | 85% |
| K-Nearest Neighbors | 82% | 82% | 88% | 85% |

A comparison of the performance of various machine learning models, namely Logistic Regression, Random Forest, SVM, Decision Tree, and KNN, was done based on some key metrics: accuracy, precision, recall, and F1-score. Of all these, the best model proved to be the Logistic Regression model, which had an accuracy of 85% with balanced precision of 86% and recall of 88%. Random Forest and SVM showed very similar performances, with high recall and resistance against class imbalance after preprocessing with SMOTE. The Decision Tree and KNN had mediocre performances where the Decision Tree tended to overfit, while the KNN was prone to false positives, being sensitive to noise. At the end, Logistic Regression turned out to be the best compromise among the three in terms of simplicity, interpretability, and predictive accuracy.

Figure (2). Correlation Heatmap: It represents the correlation between the different features of the dataset and the target variable Depression. The color bar follows the gradient where darker red reflects strong positive, darker blue represents strong negative, and lighter colors represent Weaker-correlations.

Key-Findings:

Academic-Pressure: It is moderately positively correlated with Depression, 0.47. With that in mind, high academic pressure significantly heightens the chance of depression and, therefore, one of the most critical predictors within the dataset

Work-Pressure:

High positive correlation with Job Satisfaction at **0.77**, reflecting students who have a high work pressure quite often express dissatisfaction in their jobs. While its correlation with Depression is relatively low, it means that when it comes to predicting mental health outcomes, it's going to be secondary

Financial-Stress:

Has a moderate positive value of 0.36 correlation with Depression; this clearly shows the impact that financial constraints may have on the students' mental states. This trait is a good predictor of depression.

Study-Satisfaction:

Has an inverse correlation with Depression of -0.17; this indicates that students who feel satisfied with studies are less likely to fall into depression. Its effect is relatively small, but the variable gives significant insight into mental health tendencies.

Work/study-hours:

Indicates a small positive relation, 0.21, showing that longer working or studying hours are slightly associated with poor mental health conditions. **CGPA:** Has an negligible correlation, -0.02, with Depression, which therefore tells us that CGPA does not directly influence the mental health outcome in this data. **Age:** Has a weak negative correlation, -0.23 with Depression, therefore telling us that older students within this dataset report a little lower level of depression.

Implications:

Key-Predictors:

The strongest features that act as predictors toward depression are Academic Pressure and Financial Stress. These two predictors are very important, both for training the model and for targeted interventions.

Interrelationships:

It is clear from the strong correlation between Work Pressure and Job Satisfaction that one significantly influences the other. An intervention on either could indirectly influence the other, and thus, allows for holistic strategies in mental health.

The correlation heatmap describes important relationships in this dataset, thus allowing for the identification of significant predictors of students' depression. Also, such results would permit the machine learning models to home in on the most influential factors that bring about improved accuracy and interpretability of their results. In this light, targeted mental health interventions were important to the stressors with a high significant impact on students' well-being.

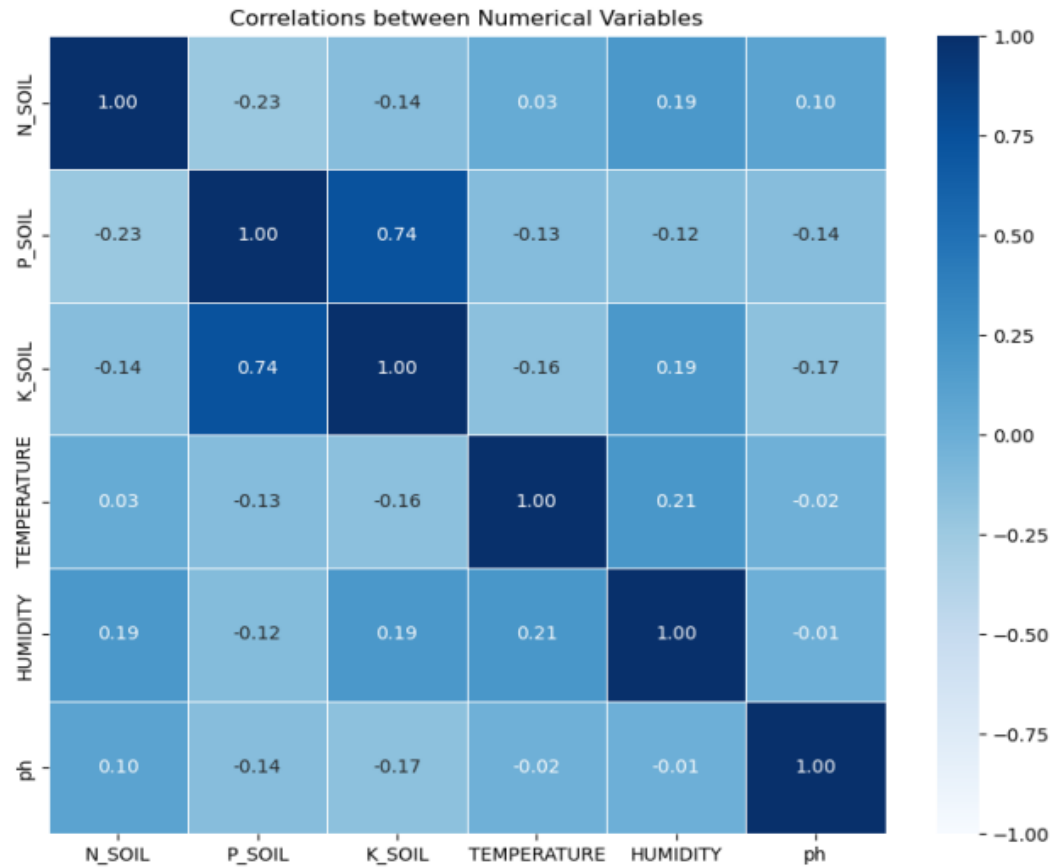


Figure 2 Correlation between the numerical variables

VI. CONCLUSION AND FUTURE WORK

This research work used machine learning to predict the factor that would best predict student depression, taking into consideration personal variables, academic performance, and lifestyle. Among the different models explored, Logistic Regression had the best performance, with an accuracy of 85%, while precision, recall, and F1-score were all well-balanced. It is interpretable and simple, which is a perfect characteristic for practical purposes. Random Forest and SVM had a very good performance, too; metrics were relatively close, hence they become strong alternatives when more complex analytics is required by different scenarios.

The study has emphasized how such preprocessing steps going into handling missing values, feature scaling, and addressing class imbalance using SMOTE greatly enhanced the equitability of models with respect to performance and their reliability. Such key predictors as Academic Pressure, Financial Stress, and Sleep Duration were identified as the factors that contribute much to student depression. Interaction variables greatly improved model performance, especially for capturing critical hidden patterns in the data.

Decision Tree and KNN showed moderate performance, which is highly prone to overfitting and noise. These results bring out the importance of model selection and optimization in sensitive problems like mental health prediction.

Despite the encouraging outcomes of this study, there remains potential for enhancement and additional investigation of the subsequent aspects:

Incorporating Real-Time Data:

Coupled with real-time data from digital learning platforms, mobile health applications, or wearable devices, this would allow for continuous monitoring and the ability to detect depression much earlier with far greater accuracy.

Complex Model Exploration:

In light of these facts, hybrid machine learning models such as XGBoost, LightGBM, and Neural Networks unmask more hidden and complex relationships for possibly better predictions. Application of Transformer-based models like BERT may also allow the assessment of a subject's mental state using text-based analysis.

Hybrid Model Development:

Thus, this would allow the strengths of models like Random Forest or Logistic Regression to be leveraged with much better interpretability through some sort of ensemble or hybrid model while improving predictive power on imbalanced datasets.

Support System Integration:

In more particular terms, that would be in the form of an end to end system working in concert with university counselling, academic advising, and healthcare services. There will be timely interference with at risk students, each with personalized suggestions of coping mechanisms or helpful resources.

Longitudinal Studies and Multi-Feature Interactions:

In this regard, the longitudinal study will indicate the change in depression over time and will provide much more value for drawing conclusions on how changes in academic and lifestyle factors lead to changes in mental health. Also, the inclusion of multi-feature interaction, such as academic pressure combined with financial stress, will increase the predictions immensely.

It is through developing these gaps that the proposed system will develop into an integrated tool in predicting and mitigating student depression, hence bringing improvement in student well-being and academic success.

REFERENCES

- [1] X.-Q. Liu, Y.-X. Guo, W.-J. Zhang, and W.-J. Gao, "Influencing factors, prediction and prevention of depression in college students: A literature review," *WJP*, vol. 12, no. 7, pp. 860–873, Jul. 2022, doi: 10.5498/wjp.v12.i7.860.
- [2] K. Hueniken et al., "Machine Learning-Based Predictive Modeling of Anxiety and Depressive Symptoms During 8 Months of the COVID-19 Global Pandemic: Repeated Cross-sectional Survey Study," *JMIR Ment Health*, vol. 8, no. 11, p. e32876, Nov. 2021, doi: 10.2196/32876.
- [3] M. Firoz, M. M. Islam, M. Shidujaman, A. Islam, and Md. T. Habib, "University student's mental stress detection using machine learning," in *Seventh International Conference on Mechatronics and Intelligent Robotics (ICMIR 2023)*, S. Patnaik and T. Shen, Eds., Kunming, China: SPIE, Sep. 2023, p. 113. doi: 10.1117/12.2690039.
- [4] R. Ahuja and A. Banga, "Mental Stress Detection in University Students using Machine Learning Algorithms," *Procedia Computer Science*, vol. 152, pp. 349–353, 2019, doi: 10.1016/j.procs.2019.05.007.
- [5] S. Inamdar, R. Chapekar, S. Gite, and B. Pradhan, "Machine Learning Driven Mental Stress Detection on Reddit Posts Using Natural Language Processing," *HumCent Intell Syst*, vol. 3, no. 2, pp. 80–91, Mar. 2023, doi: 10.1007/s44230-023-00020-8.
- [6] G. Deena, A. Sandhya, and K. Raja, "MACHINE LEARNING-BASED CLASSIFICATION AND PREDICTION OF STUDENT STRESS LEVELS: A COMPARATIVE STUDY OF ALGORITHMS," Vol., no. 19.
- [7] S. Ibbad, L. A. Baig, Z. Ahmer, and F. Shahid, "Prevalence of anxiety and depression in high school students of Karachi, Pakistan," *Pak J Med Sci*, vol. 38, no. 4, Mar. 2022, doi: 10.12669/pjms.38.4.5093.
- [8] E. M. Arias, J. Parraga-Alava, and D. Z. Montenegro, "Stress Detection among Higher Education Students: A Comprehensive Systematic Review of Machine Learning Approaches," in *2024 Tenth International Conference on eDemocracy & eGovernment (ICEDEG)*, Lucerne, Switzerland: IEEE, Jun. 2024, pp. 1–8. doi: 10.1109/ICEDEG61611.2024.10702055.
- [9] S. Sawangreerak and P. Thanathamatee, "Random Forest with Sampling Techniques for Handling Imbalanced Prediction of University Student Depression," *Information*, vol. 11, no. 11, p. 519, Nov. 2020, doi: 10.3390/info11110519.
- [10] P. Chikersal et al., "Detecting Depression and Predicting its Onset Using Longitudinal Symptoms Captured by Passive Sensing: A Machine Learning Approach With Robust Feature Selection," *ACM Trans. Comput.-Hum. Interact.*, vol. 28, no. 1, pp. 1–41, Feb. 2021, doi: 10.1145/3422821.
- [11] J. C. Cassidy, E. E. Pierson, and J. M. Starling, "Predicting Student Depression With Measures of General and Academic Anxieties," *Front. Educ.*, vol. 4, p. 11, Feb. 2019, doi: 10.3389/educ.2019.00011.
- [12] M. Faramarzi and S. Khafri, "Role of Alexithymia, Anxiety, and Depression in Predicting Self-Efficacy in Academic Students," *The Scientific World Journal*, vol. 2017, pp. 1–7, 2017, doi: 10.1155/2017/5798372.
- [13] R. Wang et al., "Tracking Depression Dynamics in College Students Using Mobile Phone and Wearable Sensing," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 2, no. 1, pp. 1–26, Mar. 2018, doi: 10.1145/3191775.
- [14] N. B. Serin, O. Serin, and L. F. Özbaş, "Predicting university students' life satisfaction by their anxiety and depression level," *Procedia - Social and Behavioral Sciences*, vol. 9, pp. 579–582, 2010, doi: 10.1016/j.sbspro.2010.12.200.
- [15] A. Singh, K. Singh, A. Kumar, A. Shrivastava, and S. Kumar, "Machine Learning Algorithms for Detecting Mental Stress in College Students," in *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)*, Apr. 2024, pp. 1–5. doi: 10.1109/I2CT61223.2024.10544243.
- [16] Uchechi Shirley Anaduaka, Ayomide Oluwaseyi Oladosu, Samantha Katsande, Clinton Sekyere Frempong, Success Awuku-Amador, "Leveraging Artificial Intelligence in the Prediction, Diagnosis and Treatment of Perinatal Depression and Anxiety: A Systematic Review," *BMJ Mental Health*, vol. 28, no. 1, Article e301445, 2025. DOI: 10.1136/bmjment-2024-301445.
- [17] Evi Zafeiridi, Malik Muhammad Qirtas, Eleanor Bantry White, Dirk Pesch, "Using Passive Sensing to Identify Depression," in *Lecture Notes in Computer Science*, vol. 14129, 2024, pp. 132–143. DOI: 10.1007/978-3-031-73741-1_9.
- [18] Gazi Hasan Al Masud, Rejaul Islam Shanto, Ishmam Sakin, Muhammad Rafsan Kabir, "Effective Depression Detection and Interpretation: Integrating Machine Learning, Deep Learning, Language Models, and Explainable AI," *Array*, vol. 10, no. 2, pp. 78–89, 2025. DOI: 10.1016/j.array.2025.100375.