

Behavioral, Life Style and Psychological Predictors of Adolescent Depression: A Machine Learning Approach

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Abstract

Adolescent depression has one of the major public health concerns due to its negative impacts on psychological well-being, academic success, and social functioning. Proactive detection of adolescent at risk is essential for timely support and assistance; however, conventional statistical methods may not adequately capture the complex nonlinear relationships among behavioral, lifestyle and psychological factors. The present study investigated the performance of five supervised machine learning approaches for predicting adolescent depression utilizing a publicly available Teen Mental Health Dataset. To improve model performance, class imbalance was addressed using Adaptive Synthetic Sampling and Bayesian optimization was applied for hyperparameter tuning. Model performance was assessed using different metrics and was further examined through learning curve analysis, repeated stratified cross validation and non-parametric statistical tests. Among evaluated models XGBoost and CatBoost achieved the best predictive performance, outperforming the remaining classifiers across all evaluation metrics. Friedman and Wilcoxon signed rank test confirmed significant differences in model performance. Model interpretation using SHAP and LIME consistently identified sleep duration, stress level, anxiety level, and daily social media use as the most important factors associated with adolescent depression. These results shows that predictive machine learning models can help to the early identification of adolescents at risk of depression while providing valuable insights into the behavioral factors associated with mental health. Such information may assist clinicians, educators and public health practitioners in developing targeted screening and early intervention strategies.

Keywords: Adolescent Depression; Explainable Artificial Intelligence; Machine Learning; Bayesian Optimization; SHAP; Behavioral Risk Factors.

1. Introduction

Adolescent mental health has been recognized as a significant global public health challenge because of increasing prevalence of depression, anxiety, psychological stress, and emotional instability among teenagers. Adolescence is a period of critical developmental stage characterized by substantial biological, emotional, cognitive, as well as social changes. In this phase, individuals are particularly vulnerable to mental health disorders that may adversely affect academic achievement, interpersonal bonding, and

overall well-being. Recent evidence suggests that symptoms of depression among adolescents have increased considerably, coinciding with the fast-paced expansion of digital platforms and social media applications. Social media has emerged as an integral component of adolescents' everyday life which facilitating communication, information sharing, and social connectivity. However, growing evidence indicates that excessive engagement with social networking platforms may negatively affect mental well-being. Studies have reported significant correlation between intensive use of social media and depression, anxiety, loneliness, reduced life satisfaction, as well as fear of missing out (FOMO) (Yue & Rich, 2023; Zsila & Reyes, 2023). Continuous exposure to idealized digital content and social comparison may lead to feelings of inferiority, low self-esteem, and emotional distress among adolescents (Dam et al., 2023; Arshad & Akhtar, 2024). In addition to social media exposure, several behavioral and lifestyle factors have been linked to adolescent depression. Previous studies have demonstrated that excessive internet use, poor sleep quality, academic stress, reduced physical activity, and heightened anxiety levels are important contributors to adverse mental well-being outcomes (Veisani et al., 2020; Lin et al., 2024; Victor et al., 2024). Sleep disturbances resulting from nighttime social media engagement have been shown to increase psychological distress, emotional dysregulation, and depressive symptoms. Similarly, reduced physical activity and excessive screen time may contribute to lower psychological well-being and increased vulnerability to depression.

Although several studies have examined the association between digital behavior and adolescent mental health, most have relied on conventional statistical techniques such as correlation analysis and regression models. While these approaches are useful for identifying associations, they may not effectively address the complexity and nonlinear relationships among behavioral, psychological, and demographic factors. Machine learning approaches presents a potential offer by promoting the identification of hidden patterns and improving predictive accuracy. However, several challenges remain unresolved, including severe class imbalance, limited hyperparameter optimization, insufficient statistical validation of model performance, and lack of model interpretability. The present study addresses these challenges by developing and comparing several supervised machine learning models for predicting adolescent depression using behavioral, lifestyle, and psychological characteristics. To improve the reliability of model development, class imbalance was addressed using Adaptive Synthetic Sampling and model hyperparameters were tuned using Bayesian optimization. Model performance was evaluated through repeated cross-validation and statistical comparison while explainable artificial intelligence was employed to analyze the relative importance of behavioral predictors and to interpret individual model predictions. By combining predictive modelling with model interpretation, this study aims not only to improve the identification of adolescents at risk of depression but also to explore the behavioral factors that are most strongly associated with depression, thereby supporting evidence-informed mental health screening and early intervention strategies.

2. Related Works

Adolescent depression has become a growing public health concern that affects emotional well-being, academic achievement and social functioning. Over the past decade, increasing attention has been given to understanding how social media use influences the psychological health of adolescents. Several studies have reported that intense involvement with social media is connected with depression, anxiety, stress, loneliness, and lower life (Hou et al., 2019; Keles et al., 2019; Zhou et al., 2023). Similarly, Masoed et al. (2021) observed that increased levels of social media addiction were associated with sleep impairments

and reduced life satisfaction among adolescents. In addition to social media use, a range of behavioral and psychological factors have been linked to depression during adolescence. Elevated stress and anxiety consistently emerged as significant predictors of depressive symptoms (Ergün et al., 2023; Unal-Aslan & Tar, 2021; Zani et al., 2024). Furthermore, poor sleep quality, excessive screen exposure, and problematic internet use have also been linked with adverse mental health related outcomes (Flynn et al., 2022; Abi-Jaoude et al., 2020). Kircaburun (2016) revealed that social media addiction may increase depression directly through excessive internet use and reduced self-esteem, whereas Tunc-Aksan and Akbay (2019) identified smartphone addiction and FOMO as important contributors to problematic social media use among adolescents. Although these studies have improved our understanding of the connection between behavioral factors and adolescent psychological health, most have relied on conventional statistical methods (Hou et al., 2019; Yamini & Pujar, 2022). While these methods are useful for identifying associations, they may not adequately capture the complex interactions among behavioral, psychological and demographic characteristics that contribute to depression.

However, recent innovations in machine learning have identified new opportunities for predicting mental health outcomes by modelling complex and nonlinear relationships among multiple risk factors. Jain et al., (2021) compared eight machine learning approaches for depression prediction using demographic, lifestyle and socioeconomic variables and reported that the SVM achieved the highest prediction accuracy which demonstrates the potential of machine learning for detecting individuals at risk of mental health disorders. Similarly, Ding et al., (2025) developed machine learning models to predict mental health outcomes among young people experiencing stressful life events. Their study showed that machine learning models, particularly a backpropagation neural network combined with SHAP based feature selection, could accurately identify important predictors such as learning pressure, adaption problems, emotional regulation and social support.

Despite these advances, several methodological challenges remain. Many previous studies have not adequately class imbalanced which can introduce imbalanced predictive models towards the majority class. In addition, systematic hyperparameter optimization towards the majority class. In addition, systematic hyperparameter optimization and statistical comparison of model performance is often overlooked and making it difficult to determine whether differences between models are statistically meaningful. Therefore, the present study addresses these gaps by developing and comparing supervised machine learning models for predicting adolescent depression using behavioral, lifestyle and psychological characteristics. Class imbalance was addressed and optimization was applied to identify optimal parameters. Further, explainable artificial intelligence was applied to analyze model predictions and detect the behavioral factors that contributed most strongly to adolescent depression.

3. Material and Methods

This study developed machine learning models to predict adolescent depression using behavioral, lifestyle and psychological characteristics. Statistical validation and model interpretation were used to evaluate the model performance and identify important risk factors. The overall workflow of the study is presented in Figure 1.

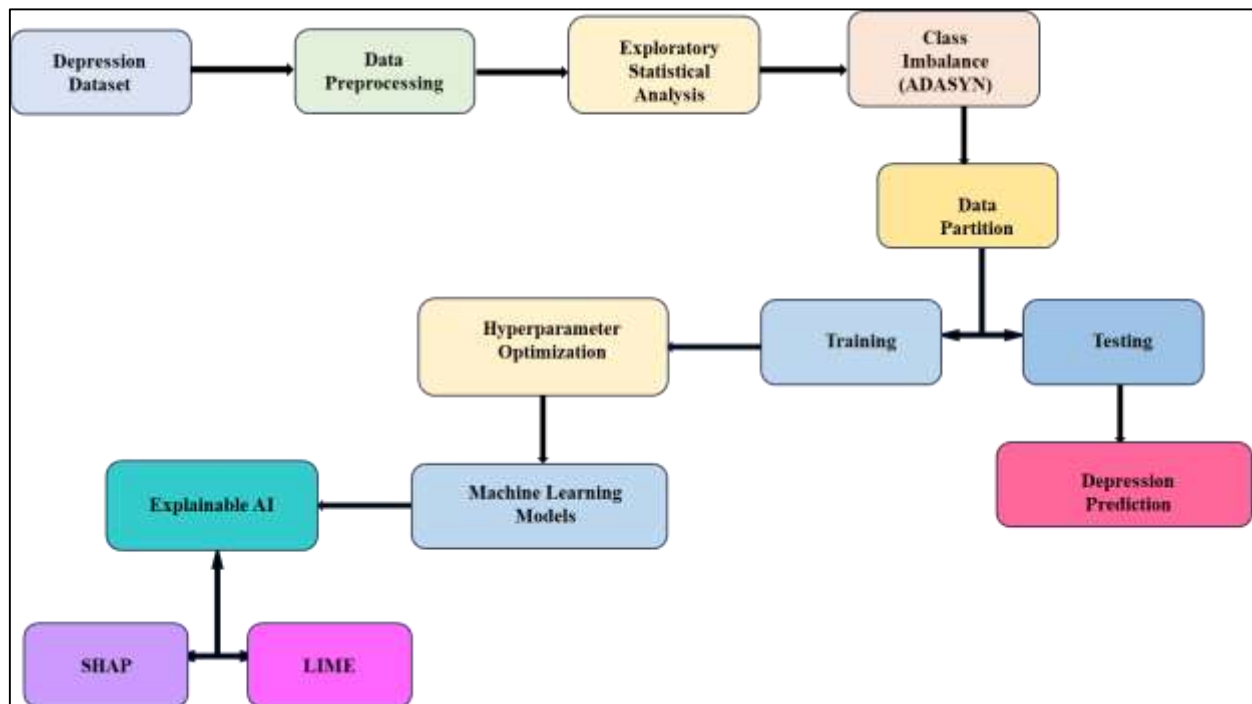


Figure 1. Schematic Workflow for the study.

3.1 Data Preprocessing

The present study used *Teen Mental Health Dataset*, which is collected from the Kaggle data repository (<https://www.kaggle.com/datasets/argonnxx/teen-mental-health>). This dataset has total of 1,200 observations, including 12 explanatory variables and 1 target variable. The 13 variables describe adolescent behavioral, lifestyle, and psychological characteristics such as age, gender, daily social media use, preferred social media platform, sleep duration, screen time before bedtime, academic performance, physical activity, social interaction level, stress level, anxiety level and depression status were considered the target variable and was represented as a binary outcome such as depressed and non-depressed adolescents. Before analysis categorical variables such as gender, platform usage, and social interaction level were transformed into numerical representations using label encoding to facilitate their use in the machine learning algorithms.

3.2 Exploratory Statistical Analysis

Prior to model development, exploratory statistical analysis was conducted to understand the characteristics of the study variables and examine their distribution. Descriptive statistics were calculated for all continuous variables. However, to assess whether significant between the two depression groups, the Mann–Whitney U test was employed. To check the relationship among the predictor correlation analysis was s performed. Additionally, multicollinearity was assessed using the Variance Inflation Factor (VIF), expressed as

	$VIF_i = \frac{1}{1 - R_i^2}$	(1)
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where R_i^2 represents the coefficient of determination obtained when the i^{th} predictor variable is regressed against the remaining predictors. A high VIF value indicates the presence of multicollinearity, which may affect the stability and interpretation of the predictive models (Chan et al., 2022).

3.3 Data Partitioning, Class Imbalance Handling, and Hyperparameter Optimization

The processed dataset was divided into training and testing sets using a stratified holdout approach, with 70:30 respectively. Stratified sampling was adopted to preserve the original class distribution in both subsets, thereby ensuring that the training and testing data were representative of the whole dataset. However, the dataset showed a marked imbalance between depressed and non-depressed adolescents, with depression cases accounting for only a small proportion of the observations. Training a classifier on such imbalanced data may bias the model towards the majority class, which may result in poor identification of adolescents at risk of depression. To address this issue, the Adaptive Synthetic Sampling (ADASYN) technique was applied to the training data (He et al., 2008). Unlike random oversampling, ADASYN generated synthetic observations primarily for minority-class samples that are more difficult to learn and allows the classifier to focus on region where misclassification is more likely.

For a minority-class observation x_i , a synthetic sample is generated as

$$x_{new} = x_i + \lambda(x_{zi} - x_i), \quad (2)$$

Where x_{zi} is one of the k -nearest neighbours of x_i belonging to the minority class, and λ is a random number uniformly distributed 0 and 1 i.e., $0 \leq \lambda \leq 1$. The number of synthetic samples generated for each minority observation is proportional to its learning difficulty, which enables ADASYN to adaptively improve the representation of underrepresented cases while preserving the local data structure.

Following the class balancing, Bayesian optimization was used to determine the optimal hyperparameter settings for each machine learning model (Wu et al., 2019). Let θ denote the set of model hyperparameters. The optimization process aims to identify

$$\theta^* = \arg \max F(\theta) \quad (3)$$

Where $F(\theta)$ represents the objective function, defined as the mean F1- score obtained through five-fold cross-validation. Bayesian optimization constructs a probabilistic surrogate model of the objective function and sequentially selects promising hyperparameter combinations by providing an efficient alternative to exhaustive search method while reducing computational cost.

3.4 Machine Learning Models

Five supervised machine learning algorithms were evaluated in this study such as Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and CatBoost were evaluated to classify adolescents as either depressed or non-depressed.

Logistic Regression (LR) models the probability of depression using the logistic function

$$P(Y = 1|X) = \frac{1}{1 + \exp \left[- \left(\beta_0 + \sum_{j=1}^p \beta_j x_j \right) \right]} \quad (4)$$

where $P(Y = 1|X)$ denotes the probability of depression, β_0 is the intercept, β_j represents the regression coefficient associated with the j^{th} predictor and x_j denotes the corresponding explanatory variable (Nusinovici et al., 2020).

Supportive Vector Machine (SVM) identifies an optimal decision boundary that maximizes the separation between the two classes. In the present study, the Radial Basis Function (RBF) kernel was employed to capture complex non-linear relationships among the behavioral variables (Han et al., 2012). The decision function is expressed as

$$f(x) = \text{sign} \left(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b \right) \quad (5)$$

Where α_i are the Lagrange multipliers, $K(x_i, x)$ is the kernel function, b is the bias term and y_i represents the class label.

Random Forest (RF) is an ensemble learning method that combines multiple decision trees constructed from bootstrap samples of the training data (Alsahaf et al., 2018). The final prediction is determined by majority voting across all trees and can be expressed as

$$\hat{Y} = \text{mode}\{T_1(x), T_2(x), \dots, T_B(x)\} \quad (6)$$

Where $T_b(x)$ denotes the prediction of the b^{th} decision tree and B is the total number of trees in the forest.

Extreme Gradient Boosting (XGBoost) is an ensemble boosting algorithm that builds decision sequentially, with each new tree correcting the prediction errors of the previous ensemble (Chen & Guestrin, 2016). The model minimizes the regularized objective function

$$\mathcal{L} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (7)$$

Where $l(\cdot)$ denotes the loss function, $\Omega(f_k)$ is the regularization term controlling model complexity and K represents the number of trees.

CatBoost is a gradient boosting algorithm designed to handle categorical variables efficiently while reducing prediction bias through ordered boosting (Azizi & Hu, 2019). Similar to other boosting methods, its objective function is given by

$$\mathcal{L} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \lambda \|w\|^2 \quad (8)$$

Where $l(\cdot)$ represents the classification loss, w denotes the model parameters and λ is the regularization coefficient used to reduce overfitting.

3.5 Performance Evaluation

The predictive performance of the developed models was evaluated using several classification metrics such as Accuracy, Balanced Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC).

Accuracy measures the overall proportion of correctly classified observations and is defined as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

Where TP, TN, FP , and FN denote the numbers of the true positives, true negatives, false positives and false negatives respectively.

Precision which reflects the proportion of correctly identified positive cases among all predicted positive cases, was calculated as

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

Whereas, Recall (Sensitivity), which measures the ability of the model to correctly identify adolescents with depression was computed as

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

The F1-score, representing the harmonic mean of Precision and Recall was used to provide a balanced assessment of model performance particularly in the presence of class imbalance. It was calculated as

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (12)$$

In addition, the ROC-AUC was used to evaluate the overall discriminative ability of each classifier across different decision thresholds. Balanced accuracy was also reported to provide an unbiased assessment of classification performance for the imbalanced dataset.

Furthermore, to assess the robustness and generalizability of the predictive models, learning curve analysis and repeated stratified five-fold cross-validation were performed. Learning curves were generated by comparing the training and validation F1-scores over progressively larger training samples. The difference between these two scores, referred to as the generalization gap was used to evaluate model stability and identify potential overfitting. Furthermore, the reliability of each model was further assessed using repeated stratified five-fold cross-validation. For each evaluation metric, the mean and standard deviation were calculated across the validation folds to examine the consistency of model performance. Finally, statistical comparison among the classifiers were conducted using the Friedman test followed by Wilcoxon signed rank tests for pairwise comparison.

3.6 Model Interpretation and Behavioral Risk Factor Identification

To better understand the factors influencing model predictions, Shapley Additive explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) were employed (Salih et al., 2025). SHAP was used to quantify the contribution of each predictor variable to the model output and to identify the behavioral factors most strongly associated with adolescent depression. The SHAP value for the i^{th} observation can be expressed as

$$f(x_i) = \phi_0 + \sum_{j=1}^p \phi_j \quad (13)$$

Where $f(x_i)$ represents the model prediction for observation i , ϕ_0 is the baseline prediction and ϕ_j denotes the contribution of the j^{th} predictor variable. The magnitude of ϕ_j reflects the relative importance of each variable in influencing the prediction. Global feature importance was determined from the mean absolute SHAP values,

$$I_j = \frac{1}{n} \sum_{i=1}^n |\phi_{ij}| \quad (14)$$

Where I_j denotes the overall importance of the j^{th} predictor. Furthermore, to complement the global interpretation, LIME was applied to explain individual predictions. LIME approximates the behaviour of

a complex prediction model in the neighbourhood of a specific observation using an interpretable surrogate model. The local explanation is obtained by minimizing

$$\xi(x) = \arg \min [L(f, g, \pi_x) + \Omega(g)] \quad (15)$$

Where f denotes the original prediction model, g is the interpretable surrogate model, $L(\cdot)$ measures the disagreement between the two models within the local neighbourhood defined by π_x and $\Omega(g)$ represents the complexity penalty imposed on the surrogate model.

4. Results and Discussion

The demographic, behavioral and psychological characteristics of the study are presented in Table 1. The study included 1,200 adolescents aged 13 to 19 years, with a mean age of 15.93 ± 2.02 years. The sample was almost equally distributed by sex, comprising 48.75 % males and 51.25 % females. Participants reported an average daily social media use of 4.54 ± 2.03 hours, while the mean sleep duration was 6.45 ± 1.44 hours, which is lower than the recommended sleep duration for adolescent. On average, participants spent 1.74 ± 0.72 hours using digital devices before bedtime. However, the mean academic performance score was 2.99 ± 0.58 , whereas the average physical activity score was 1.01 ± 0.58 . the mean stress, anxiety and addiction scores were 5.45 ± 2.90 , 5.64 ± 2.86 , and 5.57 ± 2.83 respectively which indicate moderate levels of psychological distress among the participants. Only 2.58% of the adolescents were classified as depressed, while 97.42% belonged to the non-depressed group, which demonstrating a high-class imbalance in the dataset.

Variable	Mean $\pm$ SD	Minimum	Maximum
Age (years)	15.93 ± 2.02	13	19
Daily Social Media (hours)	4.54 ± 2.03	1.0	8.0
Sleep Hours	6.45 ± 1.44	4.0	9.0
Screen Time Before Sleep (hours)	1.74 ± 0.72	0.5	3.0
Academic Performance	2.99 ± 0.58	2.0	4.0
Physical Activity	1.01 ± 0.58	0.0	2.0
Stress Level	5.45 ± 2.90	1	10
Anxiety Level	5.64 ± 2.86	1	10
Addiction Level	5.57 ± 2.83	1	10

Table 1. Descriptive statistics for demographic, behavioral and psychological variables

The distribution of the behavioral variables according to depression status is presented in Figure 2. Adolescents with depression generally reported higher levels of daily social media use, stress and anxiety together with shorter sleep duration than those without depression. The statistical test confirmed that a significant differences in daily social media use, sleep duration, stress level and anxiety between the two groups ($p < 0.001$). Whereas, age ($p = 0.704$), screen time before sleep ($p = 0.571$), academic performance ($p = 0.963$), physical activity ($p = 0.539$) and addiction level ($p = 0.627$) were not significantly associated with depression.

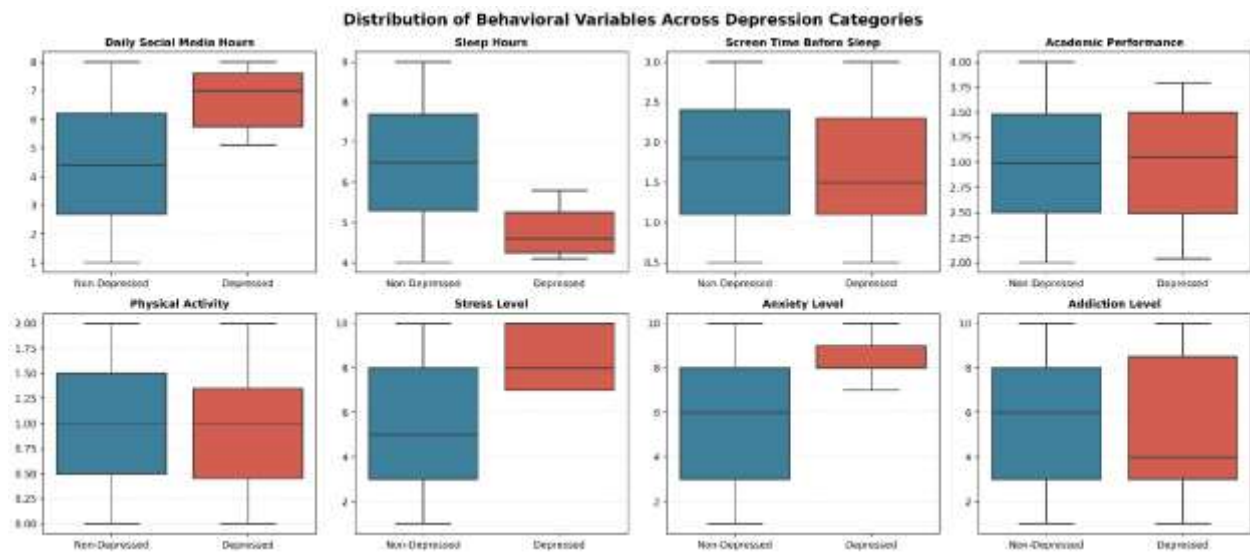


Figure 2. Distribution of behavioral variables across depression categories

The correlation matrix shown in Figure 3 indicates generally weak associations among the predictor variables, with correlation coefficients ranging from approximately -0.08 to 0.08. No strong positive or negative relationship were observed. However, the multicollinearity analysis further supported the finding. The VIF values ranged from 1.004 to 1.013 which are substantially below the commonly accepted threshold of 5. Therefore, no evidence of problematic multicollinearity was observed and all predictor variables were retained subsequent model development.

The original dataset contained substantial class imbalance, with only 2.58% of the observations representing adolescents with depression. Such imbalance can bias prediction models towards the majority class and reduce their ability to correctly identify depression cases. The effect of the ADASYN resampling technique is shown in Figure 4. After resampling the proportion of depression cases increased to approximately 50%, which is nearly a balanced training dataset. The optimal hyperparameter settings identified through Bayesian optimization are reported in Table 2. Following hyperparameter tuning, the predictive performance of the optimized models was evaluated using independent testing dataset and the results are shown in Table 3.

Table 2. Bayesian Hyperparameter Optimization Results

Model	Best Hyperparameters	Best F1	CV
Logistic Regression	$C = 1.522$	0.9640	
Support Vector Machine	$C = 22.246$, $\gamma = 0.181$, RBF Kernel	1.0000	
Random Forest	$\text{max_depth} = 9$, $\text{min_samples_leaf} = 5$, $\text{min_samples_split} = \dots$, $\text{n_estimators} = \dots$	0.9994	
XGBoost	$\text{learning_rate} = \dots$, $\text{max_depth} = \dots$, $\text{subsample} = \dots$	0.9994	
CatBoost	$\text{depth} = 6$, $\text{iterations} = 391$, $\text{learning rate} = \dots$	1.0000	

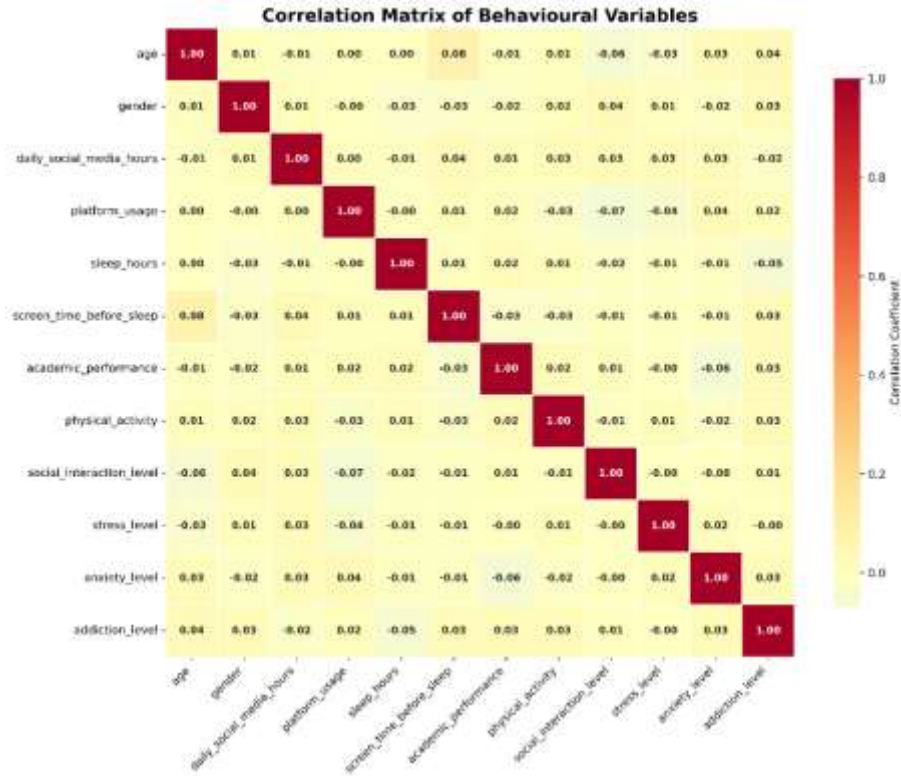


Figure 3. Correlation among Behavioral factors

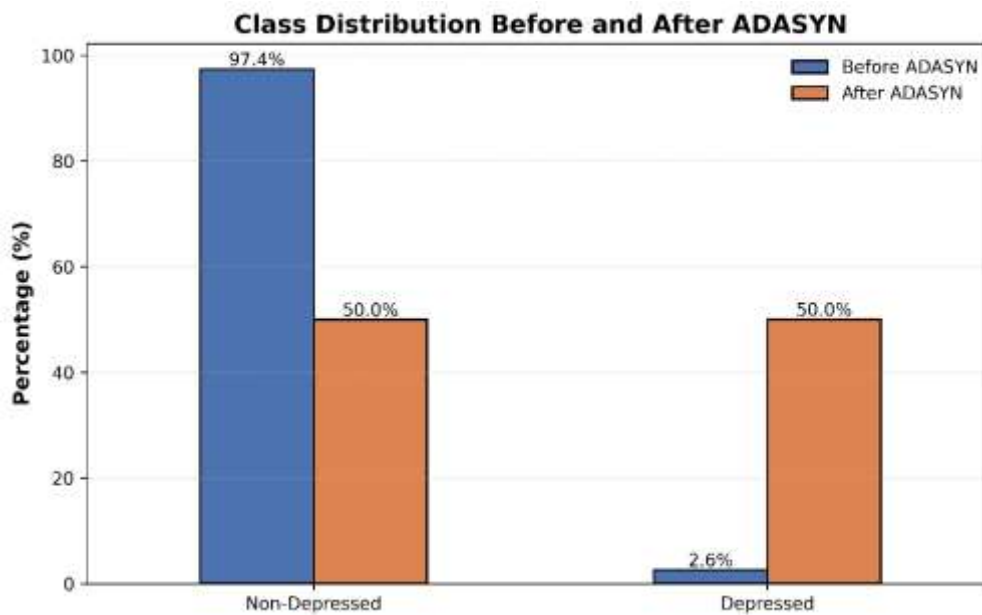


Figure 4. ADASYN class distribution plot

Model	Accuracy	Balanced Accuracy	F1	ROC-AUC
XGBoost	1.000	1.000	1.000	1.000
CatBoost	1.000	1.000	1.000	1.000
RF	0.994	0.889	0.875	1.000
LR	0.956	0.707	0.333	0.971
SVM	0.972	0.499	0.000	0.988

Table 3. Performance Comparison of Optimized Machine Learning Models

Table 4: Repeated Cross-Validation Results

Model	Accuracy (Mean $\pm$ SD)	Balanced Accuracy (Mean $\pm$ SD)	F1-score (Mean $\pm$ SD)	ROC-AUC (Mean $\pm$ SD)
LR	0.9718 $\pm$ 0.0083	0.9718 $\pm$ 0.0083	0.9721 $\pm$ 0.0082	0.9933 $\pm$ 0.0029
SVM	0.9995 $\pm$ 0.0014	0.9995 $\pm$ 0.0014	0.9995 $\pm$ 0.0014	1.0000 $\pm$ 0.0000
RF	0.9980 $\pm$ 0.0022	0.9980 $\pm$ 0.0022	0.9980 $\pm$ 0.0022	1.0000 $\pm$ 0.0000
XGBoost	0.9992 $\pm$ 0.0013	0.9992 $\pm$ 0.0013	0.9992 $\pm$ 0.0013	1.0000 $\pm$ 0.0001
CatBoost	1.0000 $\pm$ 0.0000	1.0000 $\pm$ 0.0000	1.0000 $\pm$ 0.0000	1.0000 $\pm$ 0.0000

Among the evaluated models, XGBoost and Catboost achieved the best performance by obtaining perfect values for accuracy, balanced accuracy, F1-score, and ROC-AUC. RF also performed well, with an accuracy 99.44% and an F1-score of 87.50%. While LR showed moderate predictive performance whereas SVM despite its high overall accuracy failed to correctly identify depression cases. However, the learning curves for all five classifiers are presented in Figure 5. As the training sample size increased, the training and validation F1-score gradually converged. The repeated stratified five-fold cross validation results are presented in Table 4. Among the evaluated models, CatBoost showed the highest level of stability and achieving perfect mean performance across all evaluation metrics with no observed variability. XGBoost, RF, SVM also demonstrated highly consistent performance across the validation folds whereas LR produced comparatively lower, although still satisfactory predictive accuracy.

The Friedman test indicated significant differences among the classifiers ($\chi^2 = 157.785, p < 0.001$). Pairwise comparison using the Wilcoxon signed-rank test shown in Table 5. That LR differed significantly from all other models. Significant differences were also observed between RF and the boosting-based models. However, no statistical differences were found between SVM and either XGBoost or CatBoost after Bonferroni correction, indicating comparable predictive performance among these classifiers. Figure 6. Identified sleep duration, stress level, anxiety level and daily social media use at the most influential predictors of adolescent depression. Higher stress and anxiety levels, together with increased social media use were associated with a greater probability of depression, whereas longer sleep duration appeared to have a protective effect. Further, to understand individual predictions, LIME was applied in Figure 7. Indicated that high stress and anxiety scores reduced sleep duration and prolonged daily social media use were the principal factors driving the prediction.

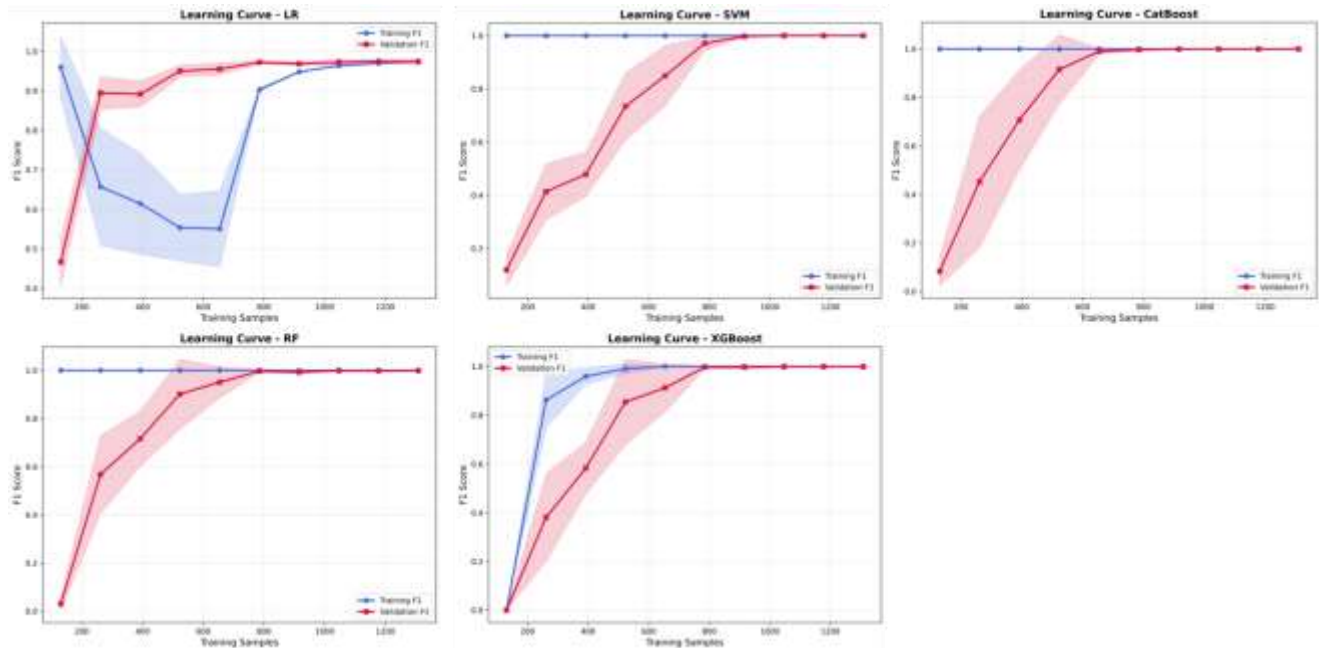


Figure 5: Learning Curves of LR, SVM, RF, XGBoost, and CatBoost

Table 5. Pairwise Wilcoxon Signed-Rank Test Results for Machine Learning Model Comparison

Model 1	Model 2	p-value	Significant
LR	SVM	<0.001	Yes
LR	RF	<0.001	Yes
LR	XGBoost	<0.001	Yes
LR	CatBoost	<0.001	Yes
SVM	RF	<0.001	Yes
SVM	XGBoost	0.0479	No
SVM	CatBoost	0.0231	No
RF	XGBoost	<0.001	Yes
RF	CatBoost	<0.001	Yes
XGBoost	CatBoost	<0.001	Yes

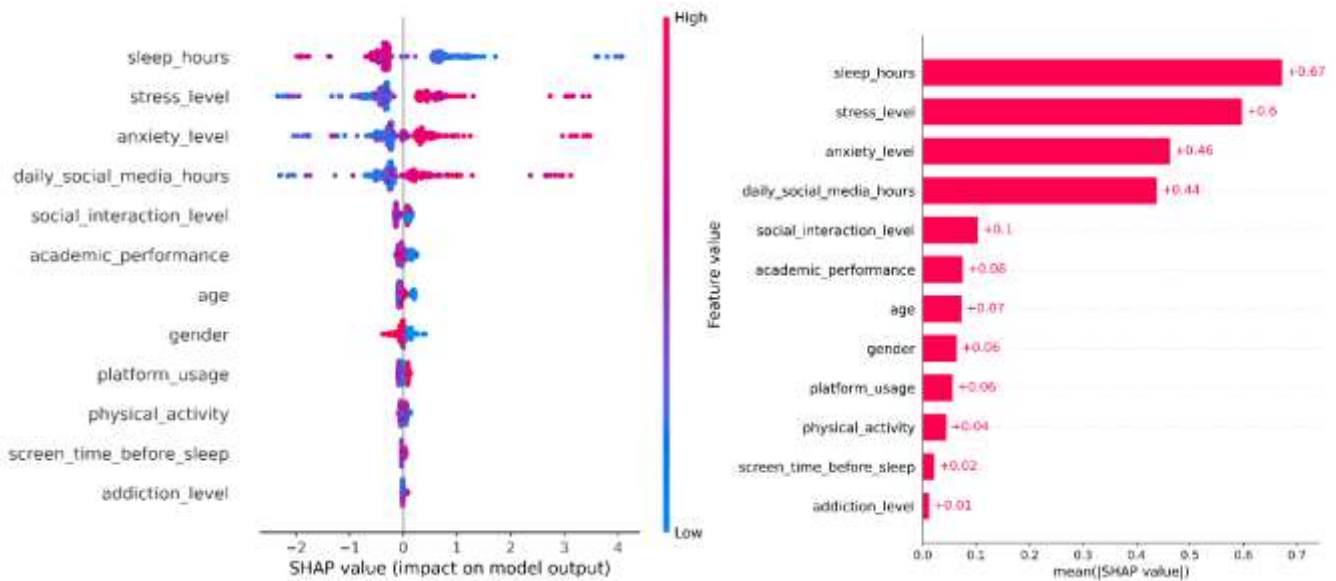


Figure 6. SHAP summary plot illustrating the impact of behavioral and psychological variables on adolescent depression prediction.

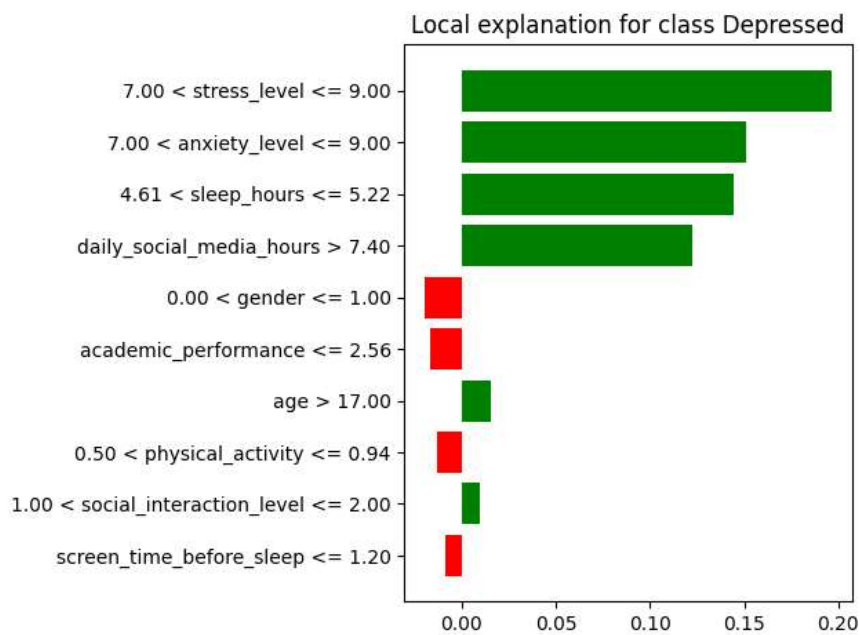


Figure 7. LIME explanation for a representative depressed adolescent showing the local contribution of behavioral and psychological factors toward the depression classification.

The findings suggest that sleep duration, stress level, anxiety level and daily social media use are the behavioral factor that most strongly associated with adolescent depression. Among these sleep durations emerged as the strongest predictor which indicates that insufficient sleep may substantially increase the risk of depressive symptoms. Whereas, adequate sleep appeared to have a protective effect on mental well-being. Elevated stress and anxiety levels also contributed markedly to depression risk which highlights the close relationship between emotional distress and depressive symptoms during adolescence. In addition, greater daily social media use was associated with a higher likelihood of depression suggests that excessive engagement with digital platforms may adversely affect psychological health. These findings

underscore the importance of promoting healthy sleep habits, effective stress management, emotional support and balanced social media use as part of strategies aimed at preventing and identifying depression among adolescent.

4. Conclusion

This study investigated the use of behavioral, lifestyle, and psychological characteristics for predicting adolescent depression using supervised machine learning models. Among the evaluated models XGBoost and CatBoost scored the highest predictive performance and demonstrates excellent classification accuracy and consistent performance during model validation. The result also showed that sleep duration, stress level, anxiety level and daily social media use were the most important factors associated with adolescent depression. Both SHAP and LIME provided consistent interpretations of model predictions and increasing confidence in the identified behavioral risk factors. Further, the observations highlighted the predictive capabilities of modelling to assist the early identification of adolescents at risk of depression. Since the most influential predictors identified in this study are largely modifiable, interventions aimed at improving sleep habits, reducing stress and anxiety and encouraging healthy social media engagement may contribute to improved mental health outcomes. Future investigations should validate the present findings using larger and more diverse participants and examine their application in school-and community-based mental health screening programmes.

5. Funding

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