



CLASSIFICATION OF DEPRESSION LEVELS IN ADOLESCENTS USING THE RANDOM FOREST ALGORITHM WITH THE SMOTE TECHNIQUE

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ABSTRACT

Adolescent mental health has become a critical issue in the digital era as increasing social media use potentially affects psychological well-being, particularly the risk of depression. Early detection of depression still faces various challenges, necessitating faster and more objective Machine Learning-based approaches. This study aims to classify depression levels in adolescents using the Random Forest algorithm combined with the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance in the data. The dataset used is the Teen Mental Health Dataset from Kaggle, comprising 1,200 samples with 12 predictor variables covering demographic factors, social media usage, and mental health indicators. The research stages include data preprocessing, an 80:20 train-test split, SMOTE application on training data, Random Forest model construction, and evaluation using Accuracy, Precision, Recall, and F1-Score metrics. Results show that the Random Forest model combined with SMOTE achieved excellent performance, with an accuracy of 99.58%, depression class precision of 100%, recall of 83.33%, and F1-score of 90.91%. Furthermore, feature importance analysis identified `sleep_hours`, `stress_level`, `daily_social_media_hours`, and `anxiety_level` as the most influential predictors in classifying adolescent depression. These findings demonstrate that the combination of Random Forest and SMOTE is effective for classifying depression levels in adolescents on imbalanced datasets.

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1. INTRODUCTION

Mental health is a fundamental aspect of one's overall health, affecting how a person thinks, feels, and acts in daily life. Among the various psychological disorders that commonly affect young people, depression stands out as a serious condition marked by prolonged sadness, emotional numbness, and disruptions in sleep and appetite [1]. Clinically, a depressive episode is identified when an individual exhibits a minimum of five relevant symptoms over a period of at least two weeks [2]. On a global scale, findings from a systematic review and meta-analysis conducted by Shorey et al. (2022) found that the prevalence of depression in adolescents worldwide reached 34%, with significant variation across regions, underscoring that adolescent depression is a transboundary public health challenge that urgently requires early intervention [3]. In Indonesia, according to the 2023 Basic Health Research (Riskesdas), the prevalence of depression in the 15–24 age group reached 2%, making adolescents a vulnerable group for mental health disorders [4].

The development of digital technology, particularly social media, has significantly changed adolescent behavior patterns. On average, teenagers today spend approximately four hours per day engaging with platforms

such as Tiktok and Instagram [1]. Excessive exposure to social media has been shown to impact sleep patterns, increase anxiety, and increase the risk of depression [5]. Evidence from a systematic review by Santos et al. (2023) further strengthens this relationship; the study confirmed that increased screen time is consistently associated with worsening psychological well-being in adolescents, including depressive and anxiety-related manifestations, well as impaired sleep quality, a condition that ultimately forms a negative cycle for mental health [6]. Furthermore, other factors such as academic pressure, low physical activity, stress levels, and digital addiction contribute to worsening mental health conditions in adolescents [7].

Conventional detection and diagnosis of depression still rely on clinical assessment by psychiatrists or psychologists. This process is relatively time-consuming, requires limited expertise, and is often hampered by social stigma, leading to many cases of depression going undetected early. Therefore, Machine Learning-based approaches are a promising alternative to support early detection of depression in a more objective, efficient, and applicable manner on a wider scale [8]. A comprehensive review by Squires et al. (2023) noted that data-driven approaches in psychiatry have shown considerable promise across detection, diagnosis, and treatment applications, though challenges related to model generalization and data representation remain [9]. Machine learning algorithms are capable of identifying complex patterns from multidimensional data that represent individual behavior and psychological conditions [10].

Random Forest is among the classification algorithms most frequently applied in machine learning research. As an ensemble approach, it operates by constructing numerous decision trees simultaneously and aggregating their outputs in order to generate a final prediction, thereby effectively reduces prediction variance and minimizes the risk of overfitting. A notable strength of this algorithm lies in its capacity to rank predictor variable according to their contribution to the model's output, commonly known as feature importance. Empirical evidence from multiple studies indicates that Random Forest tends to outperform several conventional classifiers including Naïve Bayes, Decision Tree, and K-Nearest Neighbor (KNN), particularly in problem related to mental health classification [11][12]. A major challenge in this domain, however, is class imbalance. A situation in which the number of depressed individuals within a dataset is substantially smaller than those without depression. This disparity causes models to disproportionately prioritize the majority class, leading to weak sensitivity toward underrepresented instances [13]. Aubaidan et al. (2025) highlighted that class imbalance continues to be one of the most significant obstacles in applying machine learning to health related data [14]. To address this, the Synthetic Minority Oversampling Technique (SMOTE) is commonly utilized, synthesizing artificial data points within the underrepresented class to restore distributional balanced [15].

The effectiveness of random Forest in identifying depression has been documented across a range of studies. In a study by Julita and Utomo (2025), the algorithm demonstrated exceptionally high predictive performance, reaching an accuracy of 99.97% when applied to data containing depressive symptom indicators [10]. Similarly, Pratama et al. (2025) found that Random Forest consistently surpassed competing methods including Decision Tree, Naïve Bayes, and KNN in estimating depression risk among undergraduate student [11]. On an international scale, Yu et al. (2025) evaluated Random Forest on sample of Chinese college student and recorded an AUC of 0.87, with sleep disturbance and perceived stress emerging as the two most influential predictors [16]. Meanwhile, Hairani et al. (2024) observed that SMOTE and its derivative techniques reliably strengthened model sensitivity toward underrepresented classes across multiple imbalanced health datasets [17]. At the level of comparison between algorithms, Vu et al. (2025) conducted an evaluation using national health survey data and found that Random Forest demonstrated superior performance over both XGBOOST and LightGBM under identical experimental conditions with an 80:20 train-test split evaluated using accuracy, precision, recall, and F1-score, lending further support to the methodological choices adopted in this study [18].

Although extensive research on depression classification using machine learning has been conducted, few studies have explicitly combined Random Forest and SMOTE on datasets that comprehensively capture dimensions of adolescent digital behavior. Furthermore, most studies have not quantitatively analyzed the effect of SMOTE on model performance. Digital behavior variables such as duration of social media use, platform type, and screen time before bed are also rarely used as predictors, even though these variables are increasingly relevant to the context of mental health among adolescents in today's digital era.

Grounded in the considerations outlined above, this research employs a combination of the Random Forest classifier and the SMOTE oversampling method to perform depression level classification among adolescents. The dataset utilized is the Teen Mental Health Dataset sourced from Kaggle, comprising 1200 samples and 12 predictor variables as input features for the model. This study aims to evaluate model performance using Accuracy, Precision, Recall, and F1-Score metrics, as well as analyze feature importance to identify the factors most influential in depression classification. The contributions of this research include the application of a combination of Random Forest and SMOTE on imbalanced data, providing empirical evidence regarding the influence of SMOTE on the model's ability to detect depression cases, and identifying dominant factors that can form the basis for data-based prevention and treatment of adolescent mental health.

2. METHOD

This research was conducted through several stages, beginning with dataset acquisition, followed by data preprocessing, dataset partitioning, class balancing using SMOTE, model development by applying the Random Forest algorithm, followed by model evaluation, and feature importance analysis.

2.1. Data Collection

The present study uses the Teen Mental Health Dataset, which was retrieved from the Kaggle platform. This dataset consists of 1,200 adolescents with 12 predictor variables representing demographic characteristics, social media behavioral patterns, and mental health conditions. Twelve predictor variables used include age, gender, daily social media usage, preferred social media platform, sleep duration, screen exposure before bedtime, academic performance, physical activity, social interaction level, stress level, anxiety level, and addiction level. The target variable is adolescent depression status, classified into two classes: not depressed (0) and depressed (1). This dataset was chosen because it contains factors relevant to adolescent mental health within the digital era, particularly those related to social media use, sleep patterns, stress levels, and anxiety.

2.2. Data Preprocessing

Preparing data before model training is a critical step in machine learning because data quality significantly impacts the overall quality of the model produced. This stage aims to clean and transform raw data into a suitable format to be effectively handled by classification methods. According to Syam et al. (2024), data preprocessing is the data preparation stage aimed at facilitating data processing and analysis. Preprocessing is performed to eliminate noise from the data, decrease data dimensionality, and render the data more structured [19].

Several preprocessing procedures were performed in this study. First, a check for missing values was performed using the `isnull().sum()` function on all variables to ensure there were no blank data. Second, a check for duplicate data was performed using the `duplicated().sum()` function to maintain data integrity. Third, three nominal variables (gender, platform_usage, and social_interaction_level) were converted into numeric representations using the Label Encoding method from the scikit-learn package. The method converts each categorical value into a sequential integer value so that it can be handled by the machine learning model. The results showed that the dataset contained neither missing values nor duplicate records, so all data could be used in the modeling stage without additional cleaning.

2.3. Data Splitting

In supervised machine learning, it is common practice to divide a dataset into two subsets, namely training and testing. The training subset are used to build and learn the predictive patterns within the model, while the testing data serve to assess how well the trained model performs on unseen observations. Selecting an appropriate proportion for each subset is important because it can influence the reliability and performance of the resulting model [20].

For this research, the data was split employing an 80:20 ratio, where 80% of the data were assigned to the training set and the remaining 20% were used for testing. The partitioning process was carried out using the `train_test_split()` function from scikit-learn with `test_size = 0.2` and `random_state = 42` to guarantee consistent and reproducible results. In addition, the `stratify = y` parameter was incorporated to preserve the class distribution remained proportional across both subsets.

2.4. Synthetic Minority Oversampling Technique (SMOTE)

An imbalanced class distribution represents a common issue in machine learning, particularly when a certain class contains considerably fewer observations than another. In order to overcome this problem, the Synthetic Minority Oversampling Technique (SMOTE) was employed. SMOTE is a widely used resampling approach that produces artificial examples of the underrepresented class to attain a more balanced distribution among classes. Rather than duplicating existing samples, it creates new synthetic instances through interpolation between neighboring minority-class observations [15].

In this research, SMOTE was exclusively applied to the training data following the train-test split had been completed. The implementation was performed utilizing the `fit_resample()` function provided by the `imbalanced-learn` library with `random_state = 42`. As a result, the volume of minority-class instances grew, leading to a more balanced distribution within the training data.

2.5. Random Forest Algorithm

Random Forest is an ensemble learning method that constructs several decision trees to generate predictions by reducing the variance of the new decision tree. The decision tree algorithm works by randomly drawing a set of variables (features). This collection of random trees is called a Random Forest. Random Forest is considered one of the most accurate classification algorithms, as it is capable of producing high accuracy values.

Another characteristic of Random Forest lies in its significant capability to manage imbalanced data compared to other models and its ability to identify important features in the data [21].

In the present study, the Random Forest model was built using the Random Forest Classifier class from the scikit-learn package with a hyperparameter configuration of `n_estimators=100`, meaning the model uses 100 decision trees, and `random_state=42` to ensure experimental reproducibility. Other hyperparameters, including `max_depth`, `max_features`, and `min_samples_split` use the default values from scikit-learn. The model was trained using training data that had gone through the SMOTE process (`X_train_smote` and `y_train_smote`) so that the model learns from a balanced class distribution.

2.6. Model Evaluation

Upon completing the training phase, the resulting model is assessed using four main metrics: accuracy, precision, recall, and F1 score. The selection of accuracy, precision, recall, and F1-score as evaluation metrics was based on their ability to provide a comprehensive evaluation of classification performance. Accuracy serves as a measure useful for measuring the overall correctness of predictions; however, in datasets with imbalanced class distributions, this metric alone may not sufficiently capture the model's capacity to recognize minority-class instances. Therefore, precision and recall are also considered. Precision describes how dependable the positive predictions are, while recall measures the model's effectiveness in identifying actual positive cases. In the context of depression classification, recall is particularly important because failing to detect adolescents who are truly experiencing depression may reduce the usefulness of the model for early identification. The F1-score serves to harmonize precision and recall, providing a more representative measure of performance when class distributions are uneven [22].

In addition, a confusion matrix is also employed to analyze the model's prediction results. The confusion matrix is used to calculate the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) [23]. Through this analysis, it becomes possible to determine not only the number of correctly classified instances but also the types of errors made by the model. In the context of depression classification, the confusion matrix is particularly useful for assessing the model's capacity to accurately detect adolescents with depression while minimizing incorrect labeling of depression cases as non-depression cases.

2.7. Feature Importance

Feature importance is used to identify variables that have the most significant influence on the prediction results of a machine learning model. In the context of the random forest algorithm, feature importance is measured based on each feature's contribution to impurity reduction across the entire decision tree that forms the model. Features frequently used to separate nodes in the tree will demonstrate a greater contribution to the model's final prediction [24].

Feature importance values are obtained from the `feature_importances_` attribute available in the Random Forest model. The higher the feature importance value, the greater the influence of that variable on the model's classification decisions. In this study, the feature importance values of 12 predictor variables were arranged into a DataFrame, sorted in descending order of importance, and visualized as a horizontal bar graph (horizontal bar chart) using the seaborn library.

3. RESULTS AND DISCUSSION

3.1. Dataset

The data employed in this research is the Teen Mental Health Dataset, which comprises of 1,200 recorded entries spanning 13 distinct attributes, including 12 features serving as input variables and one target variable (`depression_label`). These attributes represent demographic characteristics, digital behavior, academic performance, and mental health indicators for adolescents. Based on the results of the examination using the `isnull().sum()` and `duplicated().sum()` functions, no null entries or duplicate data existed within the dataset. Based on the data structure examination, all attributes had 1,200 valid (non-null) values, thus no missing data was found. Furthermore, the dataset consists of three data types: five float attributes, five integer attributes, and three categorical attributes, which were then converted to numeric form during the preprocessing stage. These findings suggest that the dataset possesses satisfactory data integrity and can be used directly in the next stage without requiring special handling related to data integrity.

To obtain an overview of the data characteristics, descriptive statistical analysis was performed on the numeric variables. The analysis results showed that respondents had a mean age of 15.93 years, with an average social media usage of 4.54 hours per day. In addition, the average levels of stress, anxiety, and social media addiction stood at 5.45, 5.64, and 5.57, respectively. Descriptive statistical information is shown in Table 1 below.

Table 1. Descriptive Statistics of Numerical Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Age	15.93	2.02	13	19
Daily Social Media Hours	4.54	2.03	1.00	8.00
Sleep Hours	6.45	1.44	4.00	9.00
Screen Time Before Sleep	1.74	0.72	0.50	3.00
Academic Performance	2.99	0.58	2.00	4.00
Physical Activity	1.01	0.58	0.00	2.00
Stress Level	5.45	2.90	1	10
Anxiety Level	5.64	2.86	1	10
Addiction Level	5.57	2.83	1	10

As shown in Table 1, the age range of respondents in this study ranged in age from early to late adolescence. The relatively high intensity of social media use indicates that digital activities are an important part of the respondents' lives. Furthermore, the average scores for the variables stress, anxiety, and social media addiction were at moderate levels, indicating a variety of psychological conditions that could potentially influence adolescent depression levels.

The target variable in this dataset is `depression_label`, a binary classification label, where a value of 0 represents no indication of depression and a value of 1 represents an indication of depression. The initial class distribution across the entire dataset (1,200 samples) is shown in Table 2 below.

Table 2. Distribution of Depression Label Classes in the Initial Dataset

Class (Depression Label)	Description	Number of Data	Percentage (%)
0	No Depression Indications	1,169	97.42%
1	Depression Indications	31	2.58%
Total		1,200	100.00%

Based on Table 2, a very significant class imbalance is clearly visible, where the majority class (label 0) dominates 97.42% of the entire dataset, whereas the minority class (label 1) only represents 31 samples, or approximately 2.58%. This imbalance ratio reaches more than 37:1. This imbalanced class distribution is a frequently encountered problem in mental health datasets and can cause machine learning models to tend toward favoring the majority class, resulting in misleading model evaluation outcomes for the minority class, which serves as the main target of detection. Therefore, in the next stage, the Synthetic Minority Oversampling Technique (SMOTE) approach was employed to rectify the class distribution before the model training process was carried out.

3.2. SMOTE Application Results

Before applying SMOTE, the data was first divided using a stratified split strategy with an ratio of 80:20 allocated to the training and testing subsets. This stratified split technique was chosen to maintain class proportions in both data subsets. As a result, the training data consisted of 960 samples and the test data consisted of 240 samples. SMOTE was then utilized exclusively to the training data to prevent data leakage. The distribution of classes before and after the application of SMOTE to the training set is presented in Table 3 below.

Table 3. Distribution of Training Data Classes Before and After SMOTE

Class	Before SMOTE	After SMOTE	Synthetic Sample Addition
0 (Not Depressed)	935	935	0
1 (Depressed)	25	935	910

Total	960	1.870	+910
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Based on Table 3, implementing SMOTE succeeded in balancing the distribution of classes within the training data from a ratio of 37:1 (935:25) to a ratio of 1:1 (935:935). The SMOTE technique operates by constructing new artificial instances for the underrepresented class via linear interpolation among available minority samples and their k-nearest neighbors, so that 910 new synthetic samples are successfully generated for class 1. This method is superior to simple oversampling techniques because it does not simply duplicate data, but produces new samples that are feature diverse. Consequently, the training data became more balanced and informative, providing a stronger foundation for the Random Forest model to learn depression class patterns more accurately.

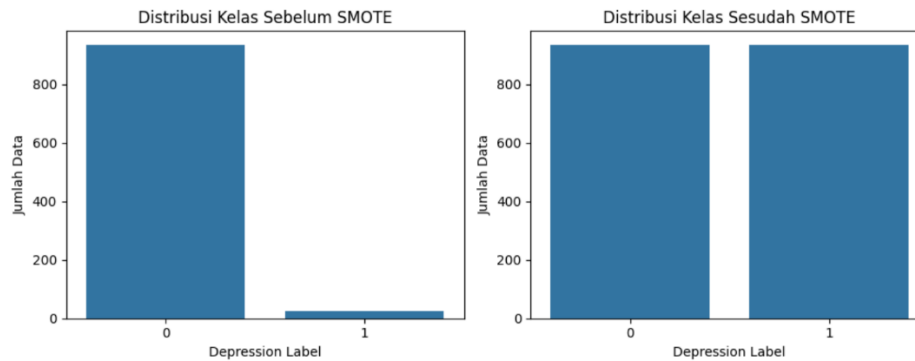


Figure 1. Class Distribution Before and After SMOTE Implementation

Changes in class distribution can also be observed through the visualization shown in Figure 1. The graph shows that before SMOTE implementation, there was a substantial disparity in the sample count across the two categories, whereas after SMOTE, the class distribution became more proportional.

The implementation of SMOTE is expected to enhance the model's ability to detect adolescents with signs of depression, particularly through increased recall and F1-score metrics within the underrepresented class. With a more balanced data distribution, the Random Forest model training process can proceed more optimally because the model is no longer overly dominated by patterns from the majority class.

3.3. Random Forest Classification Results Without SMOTE

After the preprocessing stage was completed, the Random Forest model underwent training on training data that still had an unbalanced class distribution. The model was subsequently evaluated on testing data in order to determine its classification ability without employing any data balancing techniques. The model's performance was measured through accuracy, precision, recall, and F1-score as evaluation metrics. The outcomes of this evaluation are displayed in Table 4 below.

Table 4. Random Forest Model Performance Without SMOTE

Class	Precision	Recall	F1-Score	Support
0 (Not Depressed)	97.91%	100%	98.94%	234
1 (Depression)	100%	16.67%	28.57%	6
Macro Average	98.95%	58.33%	63.76%	240
Weighted Average	97.96%	97.92%	97.18%	240
Accuracy	97.92%			

Based on Table 4, the Random Forest classifier applied without the SMOTE technique produced an accuracy value of 97.92%. Although the accuracy value obtained is relatively high, the evaluation results for each class indicate that the model still has difficulty in detecting the depression class. In the non-depression class (0), the model obtained a precision value of 97.91%, a recall of 100%, and an F1-score of 98.94%, suggesting that nearly all samples belonging to the majority class were correctly identified. However, in the depression class (1), the model only obtained a recall of 16.67% with an F1-score of 28.57%, even though the precision value reached

100%. This suggests that the model is only capable of detecting a small portion of the actual depression cases in the test data. The macro average recall value of 58.33% and the macro average F1-score of 63.76% also indicate that the overall performance of the model between classes is still unbalanced. This condition occurs because the unbalanced data distribution causes the model to tend to predominantly learn from the majority class and overlook the minority class. Therefore, a balancing approach such as SMOTE is needed to enhance the model's ability to recognize cases of depression, which are fewer in number than the non-depressed class.

3.4. Random Forest Classification Results with SMOTE

After applying SMOTE to the training data, the Random Forest model was retrained and re-evaluated on the same test data. This technique was used to augment the sample size of the minority class by generating synthetic data, thereby producing a more evenly distributed class composition. The complete classification report is displayed in Table 5, whereas the confusion matrix is illustrated in Table 6.

Table 5. Random Forest Model Performance with SMOTE

Class	Precision	Recall	F1-Score	Support
0 (Not Depressed)	99.57%	100%	99.79%	234
1 (Depression)	100%	83.33%	90.91%	6
Macro Average	99.79%	91.67%	95.35%	240
Weighted Average	99.59%	99.58%	99.56%	240
Accuracy	99.58%			

Table 6. Confusion Matrix Random Forest Model with SMOTE

	Predicted: 0	Predicted: 1
Actual: 0	234 (TN)	0 (FP)
Actual: 1	1 (FN)	5 (TP)

Based on Table 5, the evaluation results from the Random Forest model following the application of the SMOTE approach show a notable enhancement in performance relative to the model without SMOTE. The model attained an accuracy of 99.58%, indicating that most test samples were classified correctly. In the non-depressed class (0), the model attained a precision of 99.57%, a recall of 100%, and an F1-score of 99.79%. Meanwhile, in the depressed class (1), the model attained a precision of 100%, a recall of 83.33%, and an F1-score of 90.91%. The increase in recall in the depressed class from 16.67% to 83.33% indicates that the incorporation of SMOTE successfully improved the model's capacity to detect cases of depression that were previously challenging to recognize due to data imbalance. Furthermore, the macro-average recall of 91.67% and the macro-average F1-score of 95.35% indicate that the overall model performance across both classes became more balanced after data balancing using SMOTE.

These results are supported by Table 6, which presents the confusion matrix derived from the Random Forest model combined with SMOTE. From the 240 test data sets, the model successfully classified 234 non-depressive data as non-depressive (True Negative) and 5 depressed data as depressed (True Positive). Furthermore, there were no prediction errors in the non-depressive class (False Positive = 0), while only 1 depressed data set was misclassified as non-depressive (False Negative). The very small number of prediction errors indicates that the model has excellent classification capabilities. The low False Negative value also indicates that the model is capable of recognizing the majority of depression cases, thus applying the SMOTE technique has proven effective in increasing the model's responsiveness toward underrepresented classes without reducing overall classification performance in the majority class.

This outcome aligns with the results of Al Masud et al. (2025) who integrated Random Forest with data balancing techniques in depression detection and obtained 91.1% accuracy and 91.6% F1-score, confirming that combining ensemble algorithms with class imbalance handling strategies is a robust and consistent approach in the mental health classification domain [25]. Compared with that study, the model developed in this study produced higher results, attaining an accuracy of 99.58% and an F1-score of 90.91% for the depression class, thus further strengthening that the application of SMOTE is able to help the model in recognizing relatively few cases of depression and producing a more balanced and accurate classification.

3.5. Model Performance Comparison

To comprehensively assess the effect of SMOTE implementation, a comparison of both Random Forest model variants without SMOTE and Random Forest with SMOTE was directly compared on key evaluation metrics. Table 7 presents an overview of the performance difference between the Random Forest classifier before and after the use of SMOTE with respect to the accuracy, precision, recall, and F1-score metrics in the depression class.

Table 7. Comparison of Random Forest Model Performance Without and With SMOTE

Evaluation Metrics	RF Without SMOTE	RF With SMOTE	Improvement
Accuracy	97.92%	99.58%	+1.66%
Precision (Depression Class)	100.00%	100.00%	+0%
Recall (Depression Class)	16.67%	83.33%	+66.66%
F1-Score (Depression Class)	28.57%	90.91%	+62.34%

Based on Table 7, the application of the SMOTE technique had a positive impact on the overall performance of the Random Forest model in categorizing depression levels in adolescents. Before the application of SMOTE, the model produced an accuracy of 97.92%, while after the application of SMOTE, the accuracy increased to 99.58%, or an increase of 1.66%. Although the precision value for the depression class remained at 100%, the most significant increase occurred in the recall of the depression class, which increased from 16.67% to 83.33%, or an increase of 66.66%. This suggests that the model became much more adept at detecting cases of depression that were previously largely unidentified. Furthermore, the F1-score value for the depression class also rose significantly from 28.57% to 90.91%, or an increase of 62.34%. The increase in recall and F1-score demonstrate that SMOTE effectively resolved the problem of class imbalance by enhancing the model's capacity to identify minority class samples without reducing prediction accuracy. Consequently, the integration of the Random Forest algorithm with SMOTE proved to be more effective than using Random Forest without SMOTE in classifying depression levels in adolescents.

3.6. Feature Importance

An analysis of feature importance was conducted to identify the variables that provide the most significant impact on the classification of adolescent depression levels. Feature importance values in Random Forest are calculated based on the average reduction in Gini impurity produced by each variable across all decision trees in the ensemble. Table 8 presents all variables and their importance values, ranked from highest to lowest.

Table 8. Feature Importance Values for the Random Forest Model

Ranking	Variable	Importance Value	Percentage (%)
1	Sleep Hours	0.2766	27.66%
2	Stress Level	0.2360	23.60%
3	Daily Social Media Hours	0.1826	18.26%
4	Anxiety Level	0.1746	17.46%
5	Gender	0.0599	5.99%
6	Academic Performance	0.0196	1.96%
7	Social Interaction Level	0.0144	1.44%
8	Screen Time Before Sleep	0.0123	1.23%
9	Physical Activity	0.0100	1.00%
10	Addiction Level	0.0063	0.63%
11	Platform Usage	0.0042	0.42%

12	Age	0.0035	0.35%
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Based on Table 8, four variables predominantly contributed to the classification: sleep hours (27.66%), stress level (23.60%), daily social media hours (18.26%), and anxiety level (17.46%). These four variables collectively accounted for more than 86.98% of the total information used by the model in making classification decisions.

The finding that sleep hours were the most dominant predictor (27.66%) is consistent with established clinical psychology literature. Sleep disturbances, both insomnia and hypersomnia, are among the primary diagnostic symptoms of major depression. Uccella et al. (2023) demonstrated that sleep deprivation in adolescents not only impairs emotion regulation but also neurobiologically increases vulnerability to mood disorders and depression through limbic system dysfunction and cortisol dysregulation. These findings strengthen the position of sleep_hours as the most informative predictor in the adolescent depression classification model in this study [26]. Stress level ranked second, contributing 23.60%. High levels of stress in adolescents, often stemming from academic pressure, social expectations, and developmental transitions, have been identified as a key trigger for depressive episodes. The high ranking of daily social media hours (18.26%) as the third predictor has relevant implications in the context of today's adolescent digital well-being. A significant correlation was found between increased social media usage time and symptoms of depression and anxiety in adolescents, particularly through social comparison mechanisms and disrupted sleep patterns due to screen exposure. The anxiety level variable, ranked fourth (17.46%), also aligns with the extensively documented high comorbidity between anxiety disorders and depression, indicating that these two conditions exacerbate each other and often co-occur in the adolescent population.

Interestingly, the age variable ranked lowest (0.35%), with a very small contribution. This may be explained by the relatively narrow age range in the dataset (13–19 years), so age variation was not large enough to form a significant distinguishing pattern. Similarly, platform_usage and addiction_level had marginal contributions, likely because their impact on depression is more indirect and mediated by variables such as stress level and sleep hours.

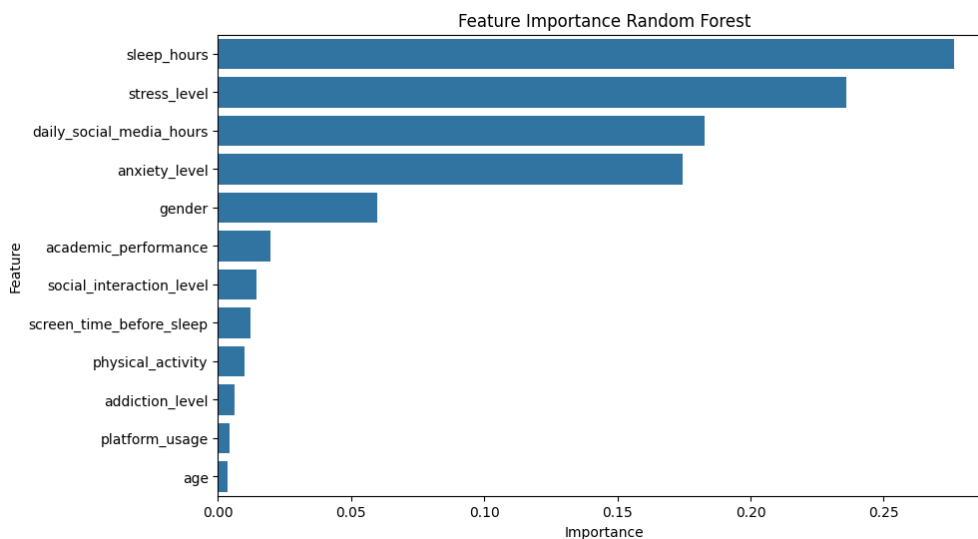


Figure 2. Feature Importance Graph of the Random Forest Model with SMOTE

Figure 2 shows a clear difference in contribution between variables. The top four variables (sleep_hours, stress_level, daily_social_media_hours, and anxiety_level) have significantly longer bars than the other variables. This visualization indicates that these four variables influence the majority of the model's decisions. Conversely, variables such as age, platform_usage, addiction_level, and physical_activity have much lower contribution values, resulting in relatively little impact on the classification results.

Combined, these four main variables contribute approximately 87% of the total feature importance value. This finding indicates that psychological conditions and daily behavioral patterns play a very dominant role in identifying depression in adolescents. Adequate sleep duration, stress levels, intensity of social media use, and anxiety levels are the factors most frequently used by the model to distinguish between adolescents with and without depression.

Overall, the results of the feature importance analysis indicate that factors related to mental health and lifestyle have a greater influence than demographic factors. Therefore, these variables can be the main focus in

efforts to detect and prevent depression in adolescents early, either through monitoring sleep patterns, managing stress, or controlling healthy social media use.

4. CONCLUSION

Drawing from the research findings, the Random Forest classifier combined with the Synthetic Minority Over-sampling Technique (SMOTE) was able to classify depression levels in adolescents with excellent performance. Implementing SMOTE successfully addressed the problem of class imbalance within the training data, enabling the model to recognize depression classes more optimally. The evaluation results showed that the model attained an accuracy of 99.58%, with a precision for the depression class of 100%, a recall of 83.33%, and an F1-score of 90.91%. These values demonstrate that the model has excellent capabilities in identifying adolescents experiencing depression and minimizing positive prediction errors. Furthermore, feature importance analysis showed that the variables `sleep_hours`, `stress_level`, `daily_social_media_hours`, and `anxiety_level` are the most influential factors in the process of classifying depression in adolescents. These findings indicate that sleep patterns, stress levels, intensity of social media use, and anxiety levels have a strong relationship to adolescent depression. Therefore, the combination of the Random Forest algorithm and the SMOTE technique can serve as an effective approach to classifying depression levels in adolescents, particularly in datasets with an imbalanced class distribution.

Subsequent studies are encouraged to utilize datasets with broader and more varied data sets to enhance the resulting model's generalizability. Furthermore, the model's effectiveness can be compared with other classification algorithms, such as XGBoost, LightGBM, CatBoost, or Support Vector Machine (SVM), to determine the most optimal model for depression classification. Future research can also explore hyperparameter optimization strategies, such as Grid Search, Random Search, or Bayesian Optimization, to further enhance model performance. Furthermore, the use of other methods for handling data imbalance, such as ADASYN or Borderline-SMOTE, as well as the addition of variables related to family circumstances, social environment, and academic factors, can be considered to produce a more comprehensive and accurate depression classification model.

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