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Combination of Synthetic Minority Over-sampling Technique (SMOTE) and Random Forest in Improving the Accuracy of Illegal Drug User Classification

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ABSTRACT

Illegal drug abuse remains a serious problem that requires analytical approaches with a high level of accuracy. In developing classification models, the imbalance in the amount of data between classes is often a major obstacle because it can cause the model to tend to classify data into the majority class. This study aims to improve accuracy and balance classification performance in identifying illegal drug users by applying a combination of the Synthetic Minority Over-sampling Technique (SMOTE) and the Random Forest algorithm. This study utilized the Drug Consumption dataset obtained from the UCI Machine Learning Repository with a total of 1,885 data points. The dataset was converted into a binary classification form, namely heroin users and non-users. Next, the data was divided into 75% training data and 25% testing data using a random sampling method. To address the problem of class imbalance, the SMOTE technique was applied to the training data to synthetically increase the number of data in the minority class. The balanced data was then processed using the Random Forest algorithm as a classification method. Model performance evaluation was carried out by comparing the classification results before and after the SMOTE application using accuracy, precision, recall, and F1-score metrics. The test results show that the application of SMOTE to Random Forest provides better performance improvements compared to the model without SMOTE. The accuracy value increased from 0.90 to 0.91, precision from 0.89 to 0.90, recall from 0.90 to 0.91, and F1-score from 0.89 to 0.90. This improvement reflects the model's more optimal ability to detect minority classes, thus minimizing bias towards the majority class. Based on these results, it can be concluded that the combination of SMOTE and Random Forest is effective in addressing imbalanced data issues and improving the overall classification performance of illegal drug users.

Keywords: accuracy, classification, imbalanced data, SMOTE, illegal drugs

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INTRODUCTION

Substance abuse, both legal and illegal, is one of the most pressing global health problems. This problem not only negatively impacts individuals' physical and mental health but also permeates various aspects of social life. Alcohol, tobacco, and drug use can affect emotional control, working memory, and reasoning skills, ultimately contributing to decreased academic performance and the emergence of risky behaviors, particularly among high school and college students. (Delgado-Lobete et al., 2020). The scale of the problem is enormous; according to the World Drug Report, approximately 5.6% of the world's population (275 million people) used drugs in 2016. Even more worrying, 31 million of these people experienced serious consequences, including increased risky sexual behavior that could potentially transmit HIV (Qiao et al., n.d.). In addition, drug abuse is often associated with increased crime rates, making effective prevention efforts a necessity to protect public stability and health..

To create effective prevention strategies, data-based evaluation of drug consumption patterns is essential (Basuni & Siregar, 2023). In the digital age, machine learning offers a powerful approach

to conducting this evaluation. Specifically, classification techniques are ideal tools for predicting and identifying individuals into specific classes, such as "users" and "non-users" of illicit drugs. These techniques work by mapping input data (e.g., demographic data and substance use history) to desired output class labels. A trained classification model generates a set of rules that can be used to identify patterns in new data and predict drug use status (Chaki et al., 2022)(Boutin et al., 2023). With this capability, classification becomes a promising solution for early detection of drug abuse.

Previous studies have demonstrated the effectiveness of machine learning in this context. Basuni and Siregar (2023) and Fernando (2025) consistently found that the Random Forest (RF) algorithm provided the best classification performance, surpassing other methods such as Artificial Neural Networks, Decision Trees, and K-Nearest Neighbor, achieving high accuracy. However, a critical gap in these studies is the neglect of class imbalance. In the drug consumption dataset used, the number of non-user data (the majority class) far exceeds the number of user data (the minority class), as shown in Figure 1 (1,605 data sets vs. 280 data sets).

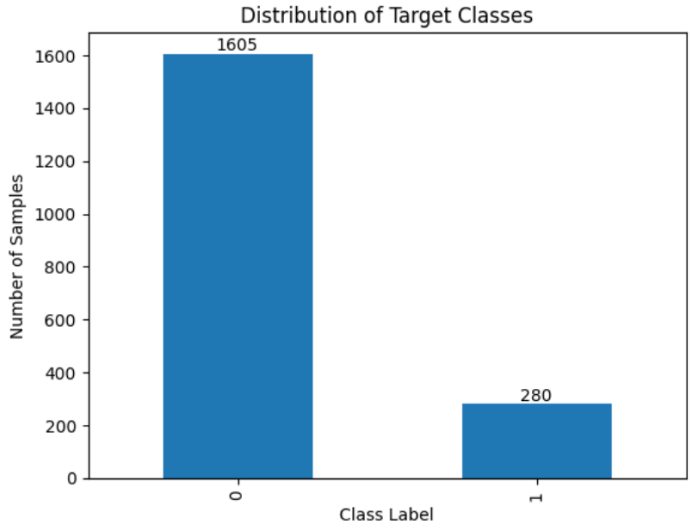


Figure 1. Class Distribution on Target Class

This condition causes the classification model to tend to be biased and classify most of the data into the majority class, thus failing to detect the minority class which is the main focus of detection (Tyagi et al., 2024). To address this challenge, this study proposes the application of the Synthetic Minority Over-sampling Technique (SMOTE) method. SMOTE is an oversampling method that has been proven effective in handling imbalanced data by generating synthetic data samples for the minority class. Several studies, such as those conducted by (Widodo et al., 2024) and (Khan et al., 2024), The results show that combining SMOTE with a classification algorithm like Random Forest can significantly improve model performance on metrics like precision, recall, and F1-score. Based on this literature review, the research problem formulation can be described in the following research questions:

RQ1: How does the Random Forest algorithm perform in classifying illicit drug users on imbalanced raw data?

RQ2: To what extent does the application of the SMOTE method improve the performance of the Random Forest classification in detecting minority classes (drug users)?

The goal of this study is to improve the accuracy and balance of the classification performance of illicit drug users by implementing a hybrid SMOTE-Random Forest method on imbalanced data. This goal is achieved by first applying SMOTE to balance the data distribution, before using the balanced data to train the Random Forest classification model. Thus, this study is expected to not only produce an accurate model but also provide a fairer and more robust solution for the early detection of illicit drug abuse.

METHOD

This study applies the Random Forest algorithm combined with the Synthetic Minority Over-sampling Technique (SMOTE) to classify legal and illegal drug consumption patterns. The research methodology is systematically structured, starting with data collection and preprocessing, including class distribution analysis. The SMOTE technique is applied to training data to address class imbalance by generating synthetic data for the minority class, followed by a classification process using Random Forest. Model performance is evaluated by comparing the classification results before and after the SMOTE application using relevant evaluation metrics, in order to objectively and reproducibly assess model performance improvements.

1. Dataset Collection

This study uses the Drug Consumption dataset obtained from the UCI Machine Learning Repository. This dataset consists of 1,885 instances representing individual characteristics related to the consumption of various types of drugs, composed of 31 attributes or features and one label that serves as the target class. The dataset was then divided into 75% training data and 25% testing data using a random sampling method consisting of seven classes in the Drug Consumption dataset, as shown in Table 1 below.

Table 1. Class Target

Class	Keterangan
CL0	Never Used
CL1	Used over a Decade Ago
CL2	Used in last Decade
CL3	Used in Last Year
CL4	Used in Last Month
CL5	Used in Last Week
CL6	Used in Last Day

2. Data Preparation

The data preparation stage is carried out after the dataset collection process and before implementing the classification method. This stage is crucial because data quality significantly impacts the performance and reliability of the classification model being built. Data preparation aims to ensure that the dataset used is valid, consistent, and representative of the problem being studied. Generally, this process includes handling missing values, feature selection in high-dimensional datasets, and addressing imbalanced class distributions. Furthermore, data preparation can also include data normalization and variable coding according to the needs of the method being used.

Based on initial exploration of the Drug Consumption dataset, no missing values were found, thus eliminating the need for imputation. However, analysis of the class distribution revealed significant imbalance, with the non-user class (label 0) accounting for approximately 85% of the data and the user class (label 1) only around 15%. To address this issue, this study implemented the Synthetic Minority Oversampling Technique (SMOTE), which generates synthetic data for the minority class through linear interpolation based on K-Nearest Neighbors. Additionally, a hold-out validation technique with random sampling was used to divide the dataset into training and test data. This division was performed before applying SMOTE to prevent data leakage, as oversampling before data separation can introduce bias and result in unrealistic model performance.

3. Handling Imbalanced Data with SMOTE

To address the class imbalance problem, this study applies the Synthetic Minority Oversampling Technique (SMOTE). SMOTE works by generating synthetic data for the minority class based on the proximity between data in the feature space. This technique is only applied to training data to avoid data leakage. By applying SMOTE, the data distribution between classes becomes more balanced, allowing the classification model to learn the characteristics of the minority class more optimally.

4. Data Classification Using Random Forest

The data classification stage is the main stage in the model learning process, where the dataset is used to learn patterns and relationships between input features and target classes. The goal of this stage is to build a model that is able to accurately classify data based on its characteristics. Classification techniques are widely used in various prediction and early detection problems, especially in cases that require precise identification of certain conditions, such as risk detection or problematic behavior. In this study, the classification process is implemented using a Classification approach included in the Supervised Learning category, where the model is trained using training data that already has class labels to learn the boundaries between classes, then used to predict classes on test data whose labels are unknown (Deepa et al., 2021) (E. et al., 2020).

The algorithm used in the classification of illicit drug users is Random Forest. This method was chosen based on previous research showing that Random Forest has superior performance compared to several other classification algorithms in similar cases. Random Forest is an ensemble learning method developed from the Classification and Regression Tree (CART) algorithm by combining bagging techniques and random feature selection in each decision tree formation. This model works by constructing several decision trees through an iterative process, where each tree is trained using a different subset of data and features. The final prediction result is determined by a majority voting mechanism from all formed trees, resulting in a more stable, accurate, and relatively resistant to overfitting model (Suryono et al., 2021).

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5. Model Evaluation

This stage is performed to evaluate the performance of the classification model using test data not involved in the training process. Model performance evaluation is performed by calculating accuracy, precision, recall, and F1-score metrics. Accuracy represents the proportion of correct predictions based on the entire test data, calculated from the number of True Positives (TP) and True Negatives (TN) compared to the total data (Wu, 2022). However, in imbalanced data conditions, accuracy alone is less representative because it tends to be influenced by the dominance of the majority class. Therefore, precision, recall, and F1-score metrics are used to provide a more comprehensive evaluation. Precision measures the accuracy of positive class predictions, recall indicates the model's ability to correctly detect positive data, while F1-score is the harmonic mean of precision and recall, reflecting the balance of model performance, particularly in identifying minority classes (Xu et al., 2020) (Heydarian et al., 2022).

FINDING AND DISCUSSION

This chapter presents the research results obtained from the data processing and classification model testing stages. The discussion includes analysis of dataset characteristics, determination of target variables and predictor features, application of the SMOTE method to address class imbalance, classification process using the Random Forest algorithm, and evaluation of model performance based on evaluation metrics and confusion matrix. The analysis focuses on the effect of SMOTE implementation on improving the classification performance of drug users and non-users, particularly in minority classes, by comparing the classification results before and after SMOTE implementation.

1. Data Collection Results

The research dataset used is the drug consumption dataset taken from UCI Machine Learning. This dataset consists of 32 features and 1,885 instances representing demographic and psychological characteristics, as well as consumption patterns of various substances. This dataset serves as the basis for the analysis and modeling of drug user classification. The features in the dataset used in this study are presented in Table 2.

Table 2. Features in the dataset

Feature types	Features name
Fitur independen	ID, Age, Gender, Education, Country, Ethnicity, Nscore, Escore, Ascore, Csore, Impulsive, SS, Alcohol, Amphet, Amyl, Benzos, Caff, Cannabis, Choc, Coke, Crack, Esctasy, Ketamine, Legalh, LSD, Meth, Mushrooms, Nicotine, Semer, VSA
Fitur dependen atau fitur target	Heroin

Based on Table 2, the Heroin feature was set as the target class, while the other features were used as independent variables. The ID feature was removed because it is unique and does not contribute to the model learning process. After feature selection, the dataset consisted of 30 independent features and 1 dependent feature. The dataset includes both numeric and categorical features as shown in Table 2. Numerical features include N-score, E-score, O-score, A-score, C-score, Impulsive, and SS, while categorical features include demographic variables and substance use patterns. All categorical features were transformed into numeric form to support the application of the SMOTE method.

As shown in Table 1, the Heroin target feature consists of seven categories (CL0–CL6). In this study, categories CL1–CL6 are combined as user classes, while CL0 is classified as non-user classes. The class distribution in Figure 1 shows data imbalance, with the non-user class (label 0) as the majority class and the user class (label 1) as the minority class.

2. Data Preparation

Data validation techniques were applied after determining the independent features and target classes. This study used the hold-out validation method to divide the dataset into training data, validation data, and test data. The data division process was carried out using random sampling, so that each instance had an equal chance of being selected and the data distribution was not affected by the dataset order. Validation data was utilized in the model selection and tuning stage, then combined with the training data after the best model was obtained. The data division resulted in a proportion of training data and test data of 75:25, with 1,413 instances as training data and 472 instances as test data, respectively.

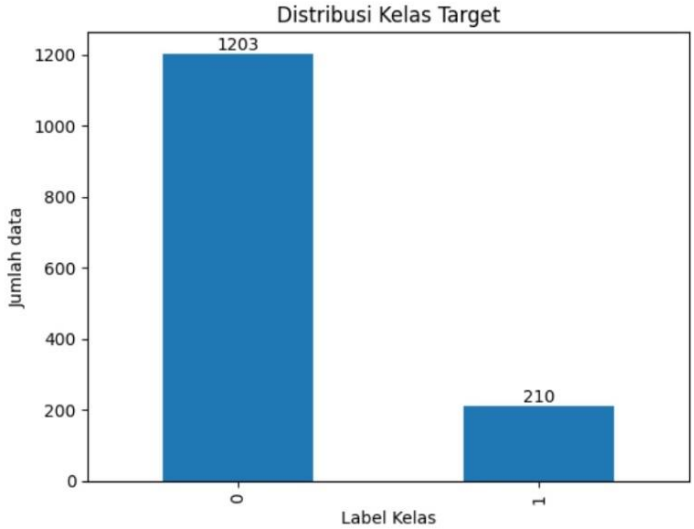


Figure 2. Target Class Distribution

Figure 2 shows the class distribution in the training data, with 1,203 instances in the non-user class and 210 instances in the user class. This distribution indicates class imbalance, making the training data the focus of the imbalanced data handling method. To address this issue, the SMOTE oversampling technique was applied to the training data.

SMOTE is implemented by generating synthetic data for the minority class until its number is balanced with the majority class. This synthetic data generation process is carried out through

linear interpolation between the minority data and K-Nearest Neighbors. The SMOTE algorithm used in the oversampling process is formulated in Equation (1), where λ is a random number between 0 and 1, X_min represents the feature vector of the minority class, and X_neighbor is one of the nearest neighbors of the minority data (Nisa et al., 2025).

$$X_{new} = X_{min} + \lambda \times (X_{neighbor} - X_{min}) \quad (1)$$

The SMOTE method was implemented using the Python programming language in the Google Collab environment. The class distribution in the training data after SMOTE application is shown in Figure 3. The oversampling results show that the number of instances in the non-user class (label 0) and the user class (label 1) each became 1,203 data. The equality of the numbers in both classes indicates that the class imbalance in the training data has been successfully overcome and the dataset is in a balanced condition.

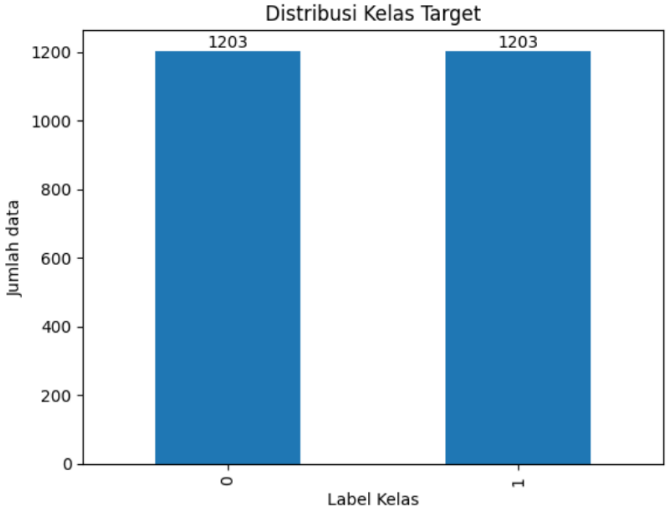


Figure 3. Class Distribution on Training Data After Applying SMOTE

Before applying the SMOTE method, the class distribution in the training data (training_data1) still showed significant imbalance, as shown in Figure 2, where the number of non-user classes (label 0) was significantly greater than the number of user classes (label 1). This condition has the potential to cause model bias towards the majority class during the learning phase. To address this issue, the SMOTE oversampling technique was applied to the training data, resulting in the training_data2 dataset. The class distribution after applying SMOTE, as shown in Figure 3, shows that the number of instances in the user and non-user classes has balanced, with 1,203 instances each.

3. Data Classification

The classification stage is carried out by applying the Random Forest algorithm to two training data scenarios: training_data1 and training_data2. Training_data1 represents training data without class imbalance treatment, while training_data2 represents training data that has been balanced using the SMOTE method. Using the same classification algorithm in both scenarios, model performance is compared to evaluate the effect of applying SMOTE on classification results.

The application of the SMOTE-Random Forest method to training_data2 is shown in Algorithm 1. The process begins by dividing the dataset into training data (D_*train*, y_*train*) and testing data (D_*test*, y_*test*). Next, SMOTE is applied to the training data to produce a balanced dataset (D_*train_smote*, y_*train_smote*). The oversampled training data is then used as input to the Random Forest model training process. The resulting model is then tested using the testing data to evaluate classification performance.

Algorithm 1. Klasifikasi SMOTE-Random Forest

Input: D (dataset), y (label kelas), T (jumlah pohon Random Forest), m (jumlah fitur acak per split), k_smote (jumlah tetangga SMOTE), ratio (rasio oversampling)

Output: Model_RF (model Random Forest), metrics (evaluasi)

1: (D_train, y_train, D_test, y_test) ← RandomSplit(D, y, test_ratio=0.25)
2: (D_train_smote, y_train_smote) ← SMOTE(D_train, y_train, k_smote, ratio)
3: Initialize Forest = ∅
For t = 1 to T:
D_bootstrap ← BootstrapSample(D_train_smote)
Tree_t ← BuildDecisionTree(D_bootstrap,m)
Forest ← Forest ∪ Tree_t
4: for each x in D_test:
predictions ← []
for each Tree_t in Forest:
predictions.append(Tree_t.predict(x))
y_pred(x) MajorityVoting(predictions)
5: ConfusionMatrix ← ComputeConfusionMatrix(y_test, y_pred)
Metrics ComputeAccuracyPrecisionRecallF1(ConfusionMatrix)

6: Return Model_RF, metrics

4. Evaluation

After training on both training datasets, training_data1 and training_data2, the classification model was evaluated using the test dataset obtained from the previous validation phase. The test dataset used in both test scenarios was identical to ensure fair and consistent comparison of model performance. Model performance was evaluated by calculating evaluation metrics and analyzing the confusion matrix to assess the model's ability to accurately classify data.

The accuracy value was calculated using Equation (2), which defines accuracy as the ratio of the number of correct predictions to the total number of predictions. The number of correct predictions is obtained by summing True Positives (TP) and True Negatives (TN), which represent predictions that match the actual class.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{T}} \qquad (2)$$

Equation (2) is used to calculate the accuracy value, which shows the proportion of predictions that are correctly classified against all test data. The accuracy value is obtained from the comparison of the number of True Positive (TP) and True Negative (TN) to the total predictions. Next, Equation (3) is used to calculate the precision value, which represents the proportion of positive class predictions that are correctly classified, namely the comparison between TP to the total positive predictions (TP and False Positive (FP)). Equation (4) is used to calculate the recall value, which measures the model's ability to correctly identify all positive class data, calculated from the comparison of TP to the total positive data (TP and False Negative (FN)). Meanwhile, Equation (5) is used to calculate the F1-score value, which is the harmonic mean between precision and recall, thus providing a measure of the balance of model performance, especially in conditions of unbalanced datasets.

$$Presisi = \frac{TP}{TP+FP} \qquad (3)$$

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

$$F1 - Score = 2.\frac{Presisi\ .Recall}{Presisi+Recall} \qquad (5)$$

The application of the classification method on training_data1 and training_data2 was evaluated using accuracy, precision, recall, and F1-score metrics calculated based on Equations (2) to (5). The evaluation was carried out by testing the results of model training on the test data. The results of the model performance evaluation for each training data are presented in Table 3. Comparison of the results in the table is used to analyze the effect of applying the SMOTE method on improving classification performance, especially in handling class imbalance.

Table 3. Classification Performance Evaluation on Test Data

Dataset	Akurasi	Presisi	Recall	F1-score
Data_latih1	0,90	0,89	0,90	0,89
Data_latih2	0,91	0,90	0,91	0,90

The results of the classification performance evaluation on the test data presented in Table 3 show that the model trained using training_data2 performed better than the model trained using training_data1. The model without SMOTE (training_data1) achieved an accuracy of 90%, a precision of 89%, a recall of 90%, and an F1-score of 89%. In contrast, the model with SMOTE (training_data2) showed improved performance with an accuracy of 91%, a precision of 90%, a recall of 91%, and an F1-score of 90%. This comparison indicates that the application of the SMOTE oversampling method positively contributed to improving classification performance across all evaluation metrics used, particularly in addressing class imbalance in the case of classifying illicit drug users.

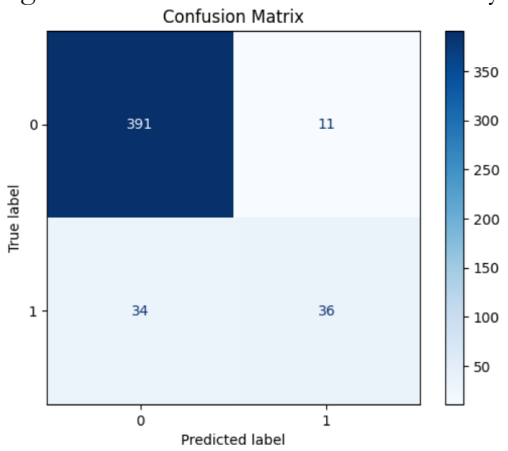


Figure 4. Confusion Matrix Results on Training Data Without SMOTE

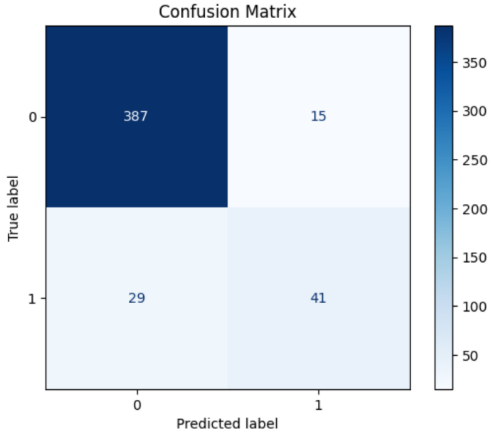


Figure 5. Confusion Matrix Results on Training Data with SMOTE

igures 4 and 5 show a comparison of classification performance on each target class before and after applying SMOTE. Figure 4 shows the classification results using training data without class imbalance treatment, while Figure 5 shows the classification results after applying SMOTE. Consistent with the results in Table 3, applying SMOTE increased the number of correct predictions for the drug user class (class 1), as reflected by the increase in recall and F1-score values, although there was a slight decrease in correct predictions for the non-user class (class 0). These findings indicate that the combination of SMOTE and Random Forest is effective in improving classification performance on datasets with class imbalance, particularly in identifying minority classes, as stated in the conclusion. These results align with the findings of (Widodo et al., 2024) who reported an increase

in precision, recall, and F1-score values on Random Forest after applying SMOTE, and is consistent with research (Khan et al., 2024) which shows that SMOTE is able to improve accuracy and F1-score in classification cases with imbalanced data.

CONCLUSIONS

The results of this study indicate that the Random Forest algorithm is capable of providing good performance in classifying drug users and non-users by utilizing the features available in the dataset. However, the imbalanced class distribution causes the model to tend to be biased towards the majority class, resulting in suboptimal detection capabilities for the minority class. To address this issue, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training data. The evaluation results show that the combination of SMOTE and Random Forest improves classification performance across all evaluation metrics, namely accuracy, precision, recall, and F1-score, with an average increase of approximately 1%. Confusion matrix analysis also shows a decrease in prediction bias towards the majority class and an increase in the model's ability to identify the minority class. These findings indicate that the application of SMOTE is effective in improving the performance of Random Forest in the case of classifying drug users under imbalanced data conditions. The results of this study can serve as a reference for the development of similar classification models and support further research in the fields of health data analysis and drug abuse.

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