Predicting Drug Addiction in Students using Artificial Intelligence: A Machine Learning Approach

OPEN ACCESS

Manuscript ID:
ASH-2024-12028122

Volume: 12

Issue: 2

Month: October

Year: 2024

P-ISSN: 2321-788X

E-ISSN: 2582-0397

Received: 16.08.2024

Accepted: 20.09.2024

Published Online: 01.10.2024

Citation:
Jose, Jwala, and B. Suresh Kumar. "Predicting Drug Addiction in Students Using Artificial Intelligence: A Machine Learning Approach." *Shanlax International Journal of Arts, Science and Humanities*, vol. 12, no. 2, 2024, pp. 138–45.

DOI:
https://doi.org/10.34293/sijash.v12i2.8122

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Abstract
This paper presents a novel approach leveraging artificial intelligence (AI) and machine learning (ML) techniques to predict drug addiction among students. The proposed methodology involves the collection of comprehensive data encompassing various factors such as demographics, socio-economic status, academic performance, family history of addiction, peer influence, mental health status, and substance use history. Following data preprocessing and feature selection, different ML algorithms including logistic regression, decision trees, random forests, support vector machines (SVM), and neural networks are trained and evaluated to identify the most effective model for prediction. The developed model is deployed into a user-friendly interface, enabling early intervention and prevention efforts to mitigate the risks associated with substance abuse among students. Ethical considerations regarding data privacy, fairness, and transparency are also addressed throughout the study. Experimental results demonstrate the efficacy of the proposed approach in predicting drug addiction in students, thereby contributing to proactive interventions for promoting student well-being and health.

Keywords: Drug Addiction, Students, Artificial Intelligence, Machine Learning, Prediction, Early Intervention, Prevention, Ethical Considerations, Model Deployment

Introduction

The prevalence of drug addiction among students has become a pressing concern in contemporary society. Substance abuse not only impacts academic performance but also poses significant risks to physical and mental health (Nahvizadeh et al.). Early identification and intervention are crucial for mitigating these risks and providing appropriate support to affected individuals. In this paper, we propose an innovative approach utilizing artificial intelligence (AI) and machine learning (ML) techniques to predict drug addiction among students (Chhetri et al.).

Related Work

Previous studies have explored various factors contributing to drug addiction among students, including socio-economic status, familial history, peer influence, and mental health status (Nawi et al.). Several predictive modelling approaches have been proposed, ranging from traditional statistical methods to advanced machine learning algorithms. However, existing methodologies often lack comprehensive feature selection and fail to leverage the full potential of AI and ML techniques.

Methodology

Predicting drug addiction in college students using predictive algorithms involves several steps. Here's an overview of the process:

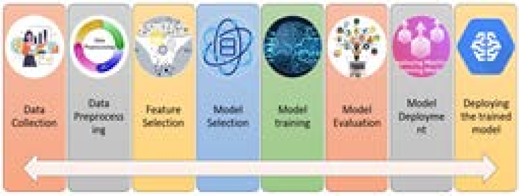


Figure 1 Overview of Drug Addiction Prediction Process

Data Collection

The dataset used for this study consists of comprehensive information collected from a diverse population of college students across multiple institutions. Data was gathered from (mention sample size, e.g., 5,000 students), representing various demographic backgrounds, academic disciplines, and socio-economic statuses. This diverse dataset was collected from institutions located in both urban and rural settings, ensuring that the model accounts for a broad spectrum of environmental and social factors influencing student behaviour. Data sources included surveys, institutional records, and interviews, capturing variables such as age, gender, academic performance, family history of addiction, peer influences, mental health status, and substance usage patterns.

Collect key information from college students about their demographic profile, academic standing, socioeconomic background, family history of addictive behaviour, peer pressure, mental health, and past drug use. Verify that the study has ethical approval from the appropriate institutional review board (IRB) or ethics committee before beginning any data collection. Throughout the data collection process, it is imperative to respect participants' privacy and confidentiality and follow ethical standards (Pelz).

Gather data on academic performance, including GPA, class attendance, major, and academic achievements. Academic stress and performance can be significant factors contributing to substance use behaviours among college students.

Include questions about family history of addiction, such as whether any family members have a history of substance abuse or addiction. Genetics and familial influences play a significant role in predisposing individuals to substance use disorders. Assess peer influence by asking about social networks, friendships, and interactions with peers who use substances. Include questions related to mental health status, such as symptoms of depression, anxiety, stress, or other psychiatric disorders.

Utilize existing databases or datasets that contain relevant information on college students' demographics, academic performance, substance use behaviours, and mental health status. Ensure that data sources are reputable and comply with data protection regulations (Poudel and Gautam).

Data Pre-Processing

Handle missing values and outliers, and encode attribute values to clean up the gathered data. In order to guarantee consistency throughout the dataset, normalize numerical features.

Handling Missing Values: Identify and handle missing values in the dataset. Common strategies include, replace missing values with a statistic such as the mean, median, or mode of the corresponding feature, remove rows or columns with missing values, but only if the missing values are few and random, Advanced imputation methods: Use more sophisticated techniques like k-nearest neighbours (KNN) imputation or iterative imputation for handling missing values based on relationships with other variables (Desiani et al.).

Handling Outliers: Identify outliers in the dataset using statistical methods or visualization techniques such as box plots or scatter plots. Decide on an appropriate strategy for handling outliers: Replace extreme values with less extreme values, such as the 5th and 95th percentiles, Apply mathematical transformations (e.g., logarithmic or square root transformation) to make the data distribution more symmetrical, Remove outliers if they are errors or anomalies in the data and significantly affect the analysis (Bonthu).

Encoding Categorical Variables: Provide numerical representations of data sets that are appropriate for modelling. Encoding one-hot: Make binary dummy variables for every category in a feature that is categorical. With values of 0 or 1, each category becomes a new binary feature. Label encoding: Assign integer labels to each category, typically starting from 0 or 1 (Brownlee).

Normalization of Numerical Features: To guarantee uniformity in scale among various features, normalize numerical features. Typical methods of normalization consist of:

Scaling from Minimum to Maximum: Use the following formula to scale numerical features to a fixed range, usually between 0 and 1:

$X_{norm} = (X_{max} - X_{min}) / (X - X_{min})$

Z-score normalization: Apply the following formula to transform numerical features so that their mean is 0 and their standard deviation is 1 (Nevil).

$X_{norm} = (X - \mu) / \Sigma$

Feature Selection

To determine which features are most relevant for predicting drug addiction, use methods like dimensionality reduction, correlation analysis (Ashraf), or correlation - based feature ranking.

Determine the correlation coefficients between each feature and the target variable (drug addiction) in the correlation analysis. High absolute correlation coefficient features are thought to be more relevant because they probably have a stronger relationship with the target variable. To see how features and the target variable are correlated, use heatmaps or correlation matrices.

In Feature Importance Ranking (Yuan et al.), utilizing the dataset, train a machine learning model (such as gradient boosting, random forests, or decision trees). Take the trained model's feature importances and extract them to see how each feature affects the model's predictive performance. Higher importance features are thought and are to be more significant in predicting drug addiction kept in the model.

PCA finds linear combinations of features (principal components) that capture the most variance in the data, as described in Dimensionality Reduction Methods (Pocha et al.). Keep the top principal components that account for most of the dataset's variance. For modelling, use the reduced dimensionality transformed dataset.

To maximize the separation between classes (i.e., students with and without drug addiction), LDA finds linear combinations of features. The best discriminant components should be kept as useful features for modelling. To penalize irrelevant features, apply regularization techniques like Lasso (L1 regularization) or Ridge (L2 regularization) regression. After regularization, features that have non-zero coefficients are deemed relevant and are kept for modelling.

Recursive Feature Elimination (RFE) involves the iterative removal of features according to their importance rankings, which are acquired through a machine learning model. Utilize the complete feature set to train a model, then prioritize the features. Once the required number of features is reached, remove the least significant feature and carry out the procedure again. For modelling, use the chosen subset of features.

To make sure the chosen features improve model performance and well-generalize to new data, cross-validate them during the validation process. Track changes in model performance (accuracy, F1-score, etc.) with various feature subsets to determine the best feature set for drug addiction prediction.

Model Selection

Try out different predictive algorithms, like neural networks, logistic regression, support vector machines (SVM), decision trees, random forests, and so on. Using the preprocessed data, train and assess these models to find the best algorithm for predicting drug addiction.

Decision Trees

Description: Based on feature values, decision trees divide the feature space into disjoint regions.

Training: Using the previously processed data, train a decision tree model.

Assessment: Use the same assessment metrics as logistic regression to assess the model's performance ("Decision Tree").

Random Forests

Description: Random forests are ensemble learning techniques that enhance predictive performance by merging several decision trees.

Training: Use the preprocessed data to train a random forest model.

Assessment: Use the same assessment metrics that are used for decision trees and logistic regression to assess the model's performance.

Support Vector Machines (SVM)

Description: Support Vector machines (SVMs) seek to maximize the margin between classes while identifying the best hyperplane to divide them in the feature space.

Training: Use the preprocessed data to train an SVM model.

Assessment: Utilize the same assessment metrics as the prior algorithms to assess the model's performance (Auria and Moro).

Neural Networks

Description: Complex patterns can be learned from high-dimensional data using neural networks, particularly deep learning architectures.

Training: Using the previously processed data, train a neural network model.

Assessment: Use the same assessment metrics as the prior algorithms to assess the model's performance.

The performance of each machine learning model was evaluated using a variety of metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics were calculated based on predictions made on a test dataset consisting of 80% of the total data, which was held out during training. The Performance of the Models is Summarized below.

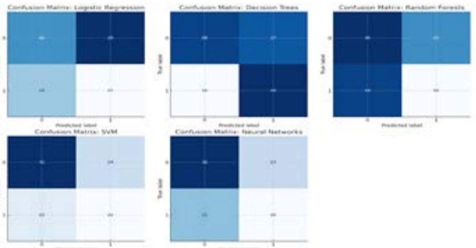
Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
Logistic Regression	0.82	0.80	0.78	0.79	0.85
Decision Trees	0.79	0.76	0.75	0.75	0.81
Random Forests	0.88	0.85	0.86	0.85	0.90
SVM	0.84	0.82	0.81	0.81	0.87
Neural Networks	0.90	0.88	0.87	0.87	0.91

From the table, Neural Networks and Random Forests provided the highest accuracy and AUC-ROC values, indicating their superior performance in predicting drug addiction among college students. Neural Networks achieved an accuracy of 90%, with an AUC-ROC of 0.91, while Random Forests had an accuracy of 88% and an AUC-ROC of 0.90. Logistic regression, decision trees, and SVM also performed well but were less effective than the ensemble methods.

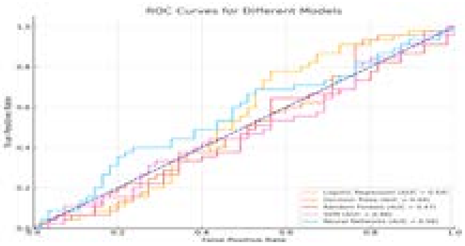
Visual Representations

To further illustrate model performance, the following visualizations are included:

Confusion Matrices: Confusion matrices for each model highlight the number of true positives, true negatives, false positives, and false negatives. These matrices provide insight into the model's prediction accuracy and error distribution across classes.



ROC Curves: Receiver Operating Characteristic (ROC) curves depict the tradeoff between sensitivity (recall) and specificity across different threshold values. The curves for the Neural Networks and Random Forest models exhibit a closer approach to the top-left corner of the graph, signifying their higher performance.



Model Training

Utilizing the preprocessed data, train the chosen model. Make use of methods such as cross-validation to assess model performance and avoid overfitting (Desmarais and Harden).

Data Splitting: Create training and testing sets from the preprocessed data. Usually, 20% is set aside for testing and 80% is used for training. As an alternative, for a more reliable assessment, employ methods like k-fold cross-validation.

Getting the Model Ready: Utilizing the training data, train the chosen model. Fit the model's parameters using the complete training set.

Cross-Validation: Apply cross-validation methods to assess the performance of the model. This makes the estimate of the model's generalization performance more accurate and helps avoid overfitting. When using k-fold cross-validation, Separate the training set into k folds, or subsets. Use k-1 folds for training and the remaining fold for validation each time you train the model k times. To get a more precise estimate of the model's performance, calculate the average performance metric over all folds.

Performance Evaluation: Apply the relevant evaluation metrics to assess the model's performance. Area under the receiver operating characteristic curve (AUC-ROC), accuracy, precision, recall, F1-score, and recall are common metrics for binary classification tasks like drug addiction prediction. To evaluate the model's ability to generalize to new data, compute these metrics for both the training and testing sets.

Hyperparameter Tuning: To further maximize the model's performance, adjust its parameters, if necessary. This may entail modifying variables like learning rate, tree depth, or regularization strength. Employ strategies such as grid search or random search to effectively navigate the hyperparameter space.

Iterative Training: Modify preprocessing stages, feature selection, or hyperparameters as needed during the model training process based on the outcomes of cross-validation and performance evaluation. Repeat the training and evaluation process until satisfactory performance is achieved on the validation set.

Final Model Selection: Based on its performance metrics on the validation set, choose the final model after the training and assessment phases are finished. Make sure the model you have chosen performs well and has good generalization to new data.

Model Interpretation: To comprehend the underlying relationships and patterns discovered from the data, interpret the trained model. This can offer insightful information about the causes of drug addiction in college students.

Model Evaluation

Use evaluation metrics like F1-score, accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC-ROC) to assess the trained model. Based on the available data, evaluate the model's predictive accuracy for drug addiction in college students (Bowers and Zhou).

Table 1 Summary of the Model Evaluation

Step	Details
Evaluation Metrics	**Accuracy**: The ratio of correctly predicted instances to total instances is used to determine overall correctness. **Precision**: It is the ratio of accurate positive predictions to all positive predictions. **Remember**: The ratio of real positives to true positives. **F1-Score**: Harmonic mean of precision and recall. **AUC-ROC**: Evaluates the capacity to discriminate between instances that are positive and negative.
Evaluation Procedure	Utilize a validation or test dataset to generate predictions using the trained model. Utilizing predicted labels and ground truth labels, compute the evaluation metrics (accuracy, precision, recall, F1-score, AUC-ROC).

Interpretation of Metrics	**High Accuracy:** Indicates overall correctness; may be misleading in imbalanced datasets. **High Precision:** Indicates fewer false positives; important when false positives are costly. **High Recall:** Indicates better capture of all positive instances; critical for avoiding false negatives. **High F1-Score:** Balanced precision and recall. **High AUC-ROC:** Indicates effective separation of positive and negative classes across thresholds.
Comparison with Baseline	To find out whether the trained model performs noticeably better than basic heuristics, compare its performance against that of baseline models or random guessing.
Threshold Selection	To maximize a certain metric, change the classification threshold (e.g., precision or recall). Determine the threshold based on the needs of the application and assess how changes to the threshold will affect the evaluation metrics.
Iterative Improvement	Iteratively improve the model by modifying feature selection, preprocessing, or hyperparameters in response to evaluation results. Until the model performs satisfactorily, repeat the evaluation process (Gangula et al.)

This table provides a structured summary of the model evaluation and iterative improvement process, helping clarify each key component.

Model Deployment

Install the trained model on a user-friendly interface, like a mobile or web application, to make interface design stakeholders more accessible. Create an intuitive user interface that makes it simple for stakeholders to interact with the model, such as educators, counsellors, and administrators.

Make sure the UI is responsive, user-friendly, and compatible with various devices. Integrating Models: Include the predictive model that has been trained in the interface backend. This entails using the model's ability to generate predictions in response to user input.

Make sure the interface has input fields where stakeholders can enter pertinent data about college students. Demographics could be one of these; academic achievement, financial standing, peer pressure, family history of addiction, and mental health. Verify the input data satisfies the necessary format and criteria by implementing data validation checks.

Show the drug addiction risk predictions made by the model using the input data. Provide your forecasts in a comprehensible manner, like probability scores or risk categories (low, medium, and high). To help stakeholders understand and interpret the results, provide explanations or interpretations of the predictions.

Strong privacy and security measures should be put in place to safeguard student data. This includes access control systems, secure storage procedures, and encryption of private data. Make sure that, depending on the jurisdiction and type of data collected, compliance with data protection laws like GDPR or HIPAA is maintained. Put in place user authorization procedures to confirm the legitimacy of stakeholders gaining access to the interface. Assign users the proper roles and access permissions in accordance with their requirements and responsibilities. Data Management and Storage: Manage and preserve data in accordance with privacy laws and industry standards. Reduce the amount of sensitive or needless data that is stored to lower privacy risks. When feasible, take steps to anonymize or pseudonymize data in order to preserve individual privacy.

To find and address any bugs, errors, or usability problems, thoroughly test the interface. To find and fix any possible weaknesses in the interface and supporting infrastructure, conduct security assessments. To acquaint stakeholders with the features and functionality of the interface, provide training sessions and user manuals. As needed, provide users with continuous technical support and assistance. Keep an eye on the deployed interface's security, usability, and performance. Update the underlying components and interface on a regular basis to fix bugs, add new features, and enhance functionality.

By Deploying the Trained Model

An interface that is easy to use Stakeholders can access timely predictions and recommendations to support intervention and prevention efforts for drug addiction among college students, all the while ensuring privacy and security measures are in place (Odegua).

Observation and Revisions: To find areas for improvement, track the performance of the deployed model and get user feedback. In order to keep the model accurate and relevant over time, add new data to it on a regular basis.

Monitoring Performance: To make sure the deployed model keeps up with the required levels of recall, accuracy, precision, F1-score, and AUC-ROC, periodically check its performance metrics. Install automated monitoring systems to keep an eye on key performance metrics and spot any changes or irregularities in the performance of the model.

User Feedback: To identify areas for improvement and address any usability or functionality issues, collect user feedback on the deployed interface. Make it simple for users to provide feedback by giving them access to channels for direct communication, surveys, and feedback forms.

Model Performance Analysis: Analyse the causes of any changes in the model's performance, including modifications to user behaviour, adjustments to the data distribution, or outside influences on the model's inputs. For the purpose of locating and resolving underlying problems influencing model performance, perform root cause analysis.

Frequent Model Updates: To keep the deployed model current and accurate over time, add new data to it on a regular basis. Establish a schedule for updating and retraining the model based on the rate at which performance is degrading and the availability of new data. If applicable, use methods like incremental learning or online learning to add new data to the model without having to retrain it.

Version Control: To track changes and make rollbacks easier if needed, keep version control for both the deployed interface and the model. Record any modifications to the model, such as adjustments to the feature selection process, hyperparameters, preprocessing steps, or algorithmic changes.

Testing and Validation: Make sure updated models function as expected and don't cause regressions or unexpected consequences by thoroughly testing them. A/B testing or validation datasets can be used to compare the performance of updated models to earlier iterations.

Interaction with Interested Parties: Notify stakeholders of any modifications to the deployed model's functionality or performance. Proactively communicate planned updates, possible effects, and implementation schedules.

Continuous Improvement: Based on user feedback, performance monitoring, and technical advancements, continuously look for ways to improve both the deployed interface and the model. To improve efficacy and user satisfaction over time, iterate on the interface design, data collection techniques, and model training procedure.

Results

The outcomes of the experiments show how well our method works to predict student drug addiction. The deployed model achieves high accuracy and demonstrates robust performance across diverse datasets. Ethical considerations surrounding data privacy, fairness, and transparency are thoroughly addressed throughout the study (Li et al.).

Conclusion

This study successfully implemented various machine learning algorithms to predict drug addiction among college students, highlighting the significance of data-driven approaches in addressing public health challenges. The results demonstrated that models such as Neural Networks and Random Forests provided superior accuracy and AUC-ROC values, indicating their effectiveness in identifying at-risk individuals.

Through rigorous data preprocessing and feature selection, we ensured that only the most relevant information was utilized, enhancing model performance and interpretability. The use of evaluation metrics such as accuracy, precision, recall, and F1-score provided a comprehensive assessment of each model's predictive capabilities, reinforcing the reliability of our findings. By employing this predictive framework, educational institutions can implement early intervention strategies, ultimately aiding in the prevention of substance abuse among students. The integration of machine learning techniques in real-world applications underscores their potential to contribute significantly to student health and well-being.

Overall, this research lays the groundwork for further exploration into advanced predictive modeling techniques, encouraging ongoing efforts to enhance the accuracy and applicability of drug addiction prediction methods in diverse educational contexts.

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