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Enhancing Drug Detection Strategies for Post-Rehabilitated Juveniles: A Comprehensive Review and Empirical Study

Priyanka Kaushik
Dept. of Computer Science Engineering
Chandigarh University
Chandigarh, India
kaushik.priyanka17@gmail.com

Prabha Gour
Dept. of Humanities & S.Science
Madhav University
Pindwara, India

Lovish Bir
Dept. of of Com. Science Engineering
Chandigarh University
Chandigarh, India
lovishbir@gmail.com

Lubna Ansari
Dept. of Computer Eng. & Applications
Mangalayatan University
Aligarh, India
lubna.ansari@mangalayatan.edu.in

Rojalini samnata
Dept. of Pharamcy
Usha Martin University
Jharkhand, India
rojalinsamanta91@gmail.com

R.Soundarya
Dept. of Biomedical Engineering
Dhanalakshmi Srinivasan college
Coimbatore, India
rahesorasoundarya@gmail.com

***Abstract*—Drug addiction is a complex problem that will affect individuals of all ages, including juveniles. It is a chronic and often relapsing disease that requires continued care and support to help individuals achieve and maintain long-term recovery. While rehabilitation programs are designed to help individuals overcome addiction, relapse rates remain high, making post-rehabilitation drug detection an important component of continued care. This study aims to investigate the efficacy of various drug detection techniques for juveniles who have completed their rehabilitation. The success of rehabilitation program for young drug addicts depends on the creation of efficient drug detection rules and procedures that can assist avoid relapse and increase program effectiveness overall. The research technique comprises both an empirical investigation of post-rehabilitated juvenile participants and a thorough evaluation of the literature of past studies on drug detection for young people. The results of this study will have a big impact on how well drug detection policies and practises for young people who have completed their rehabilitation are developed.**

***Index Terms*—Drug, Addiction, Rehabilitation, Post Rehabilitated**

I. Introduction

Juvenile drug use is a serious public health issue that can have long-term effects on a person's mental, physical, and social health. While drug rehabilitation programs can be effective in treating addiction, detecting drug use in post-rehabilitated juveniles is critical to ensuring long-term recovery and preventing relapse. Traditional drug testing methods, such as urinalysis, blood tests, and hair analysis, have limitations in terms of accuracy, reliability, and sensitivity, which can lead to false positives or negatives. Machine learning is a rapidly developing technology that can improve the accuracy and effectiveness of drug detection in post-rehabilitated juveniles. Machine learning algorithms can analyze large datasets of drug use patterns and identify subtle changes that may indicate relapse. Additionally, machine learning can be used to develop more personalized drug testing protocols based on an individual's history of drug use and other factors. This study's goal is to examine how machine learning is used to identify drugs in post-rehabilitation juveniles. The prospective uses of machine learning in drug detection will be specifically discussed in this study, including the creation of wearable gadgets that can continuously monitor drug use., the analysis of social media data to identify potential triggers for relapse, and the use of machine learning to develop more accurate and reliable drug testing protocols.

By examining the current state of drug detection in post-rehabilitated juveniles and the potential applications of machine learning, this research paper will contribute to the development of more effective drug testing protocols and the implementation of new drug detection technologies. The findings of this study may also have implications for policymakers, clinicians, and researchers who are interested in improving the outcomes of drug rehabilitation programs for juveniles. Ultimately, the goal of this research is to promote a better understanding of the potential applications of machine learning in drug detection and rehabilitation and to improve the long-term recovery of post-rehabilitated juveniles.

II. Literature Review

R. Dong et al. (2015) combined dynamic surface-enhanced Raman spectroscopy with support vector machines for drug detection in human urine, providing a rapid and sensitive analytical method [1]. S. Belenko and T. Logan (2003) evaluated juvenile drug court models, emphasizing the need for enhanced treatment strategies to address substance abuse among ado-

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lescents effectively [2]. European Economic Letters (2024) comprehensively reviewed juvenile delinquency, focusing on rehabilitation strategies and correctional approaches to reduce recidivism rates in youth populations [3]. S. Dara et al. (2021) reviewed machine learning applications in drug discovery, highlighting the transformative impact of AI-driven tools on accelerating and optimizing drug development processes [4]. J. B. Sander et al. (2012) conducted a meta-analysis on juvenile delinquency interventions, revealing positive effects on improving academic outcomes for at-risk youth [5]. D. Pardini (2016) proposed empirically based strategies for preventing juvenile delinquency, emphasizing early intervention and community-based programs to mitigate risk factors [6]. R. Rathore (2023) analyzed healthcare system efficiency using the M/M/C queue model, demonstrating the importance of occupancy management in optimizing hospital resource utilization [7]. S. Soni et al. (2022) reviewed advances in aptasensing technologies for detecting illicit drugs, underlining their potential for sensitive, real-time applications in drug monitoring [8]. J. E. Becan et al. (2020) explored the complexity of process improvement plans in substance use services for justice-involved youth, offering insights into service delivery optimization [9].

R. Rathore and S. P. S. Rathore (2024) investigated machine learning applications in HR, focusing on predictive analytics for employee turnover and performance, aiding decision-making in workforce management [10]. Q. Sun et al. (2016) developed an anti-biofouling silica-micelle membrane enabling drug detection in whole blood, contributing to advancements in diagnostic and bioanalytical methods [11]. D. M. Stein et al. (2015) conducted a meta-analytic review on the effectiveness of juvenile treatment drug courts, emphasizing their positive impact on adolescent substance abuse treatment and rehabilitation outcomes [12]. R. L. Izzo and R. R. Ross (1990) examined rehabilitation programs for juvenile delinquents through a meta-analysis, demonstrating the effectiveness of structured interventions in reducing recidivism and promoting positive behavioral changes [13]. D. Prakash (2024) explored how big data analytics influences organizational performance, highlighting its potential to optimize decision-making, improve operational efficiency, and enhance overall business outcomes [14]. L. Mitchell et al. (2021) developed a versatile fluorescent sensor array for detecting platinum-based anticancer drugs in biological fluids, showcasing an innovative approach to drug monitoring in clinical settings [15]. C. Williams et al. (2021) tested an evidence-based drug abuse and violence prevention approach for youth in juvenile justice diversion programs, yielding promising results for reducing substance use and violence among at-risk adolescents [16]. W. Jiang et al. (2021) investigated graphene-based composites for electrochemical sensor fabrication, offering a novel application in drug detection that enhances the sensitivity and selectivity of detection methods [17]. R. F. Kranenburg et al. (2020) presented a handheld near-infrared spectrometer coupled with machine learning for on-site cocaine detection, providing a rapid and robust solution for field drug testing [18].

M. Al Malki (2023) reviewed the sustainable growth challenges faced by small and medium enterprises, addressing key obstacles such as financial management, market access, and regulatory compliance [19]. M. S. Nasir and M. E. Jolley (1999) explored fluorescence polarization as an analytical tool in immunoassays and drug discovery, contributing to advancements in biomolecular detection and diagnostic applications [20]. C. W. Harris and L. Wylie (2021) studied drug testing policies in pretrial diversion programs for juveniles, finding that successful outcomes were closely tied to effective drug testing practices and appropriate interventions [21]. D. M. Haddab (2023) examined data-driven decision-making in manufacturing businesses in China and the Asia-Pacific region, highlighting how data analytics enhances operational efficiency and strategic planning in the industrial sector [22]. Sikarwar et al. (2024) leverage OpenCV and IoT technologies for enhanced lane management in smart environments, contributing to smart transportation systems by improving traffic flow and safety through automated monitoring [23]. CNN-Based Brain Hemorrhage Detection in Intelligent Environments (Tanwar et al., 2024) Tanwar et al. (2024) explore the use of Convolutional Neural Networks (CNNs) for detecting brain hemorrhages in intelligent healthcare systems, improving diagnostic accuracy in medical imaging and emergency care [24]. Smart Road Segmentation from Aerial Images (Kaushik et al., 2024) Kaushik et al. (2024) focus on road segmentation using aerial images, combining computer vision and machine learning to enhance smart city infrastructure, traffic management, and urban planning [25]. Smart Technology for User-Centric Movie Recommendations (Kaushik et al., 2024) Kaushik et al. (2024) examine how smart technologies can improve user-centric movie recommendations, applying AI algorithms to personalize viewing experiences, enhance user satisfaction, and drive engagement in digital platforms [26].

III. METHODOLOGY

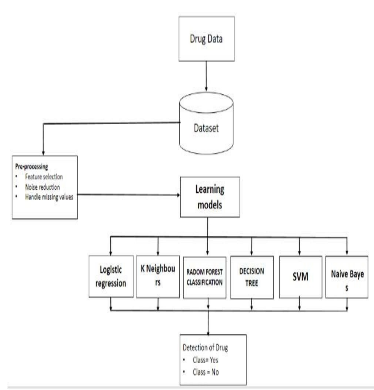

Fig. 1. Work Flow Diagram

Figure 1 depicts the work flow of the project and the methods involved as mentioned below

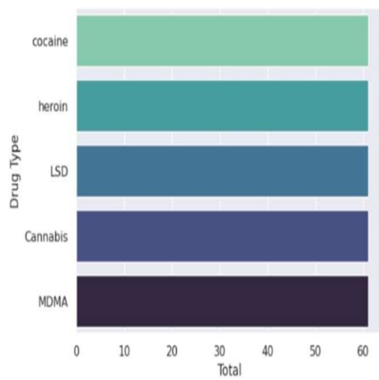

Fig. 2. Smote Technique

A. Data Collection

The foundation of a machine learning-based drug detection system lies in acquiring a large and diverse dataset of drug samples. Data can be collected from a variety of sources, including:

- Hospitals: For clinical drug records and usage patterns.
- Drug Rehabilitation Centers: For data on drugs commonly abused and recovery patterns.
- Law Enforcement Agencies: For information on confiscated drugs, their dosages, and forms.

1) The dataset should encompas:

- Different Drug Types: Samples of various drugs, including commonly abused substances.
- Dosages and Purity Levels: Variations in drug potency and concentration to ensure robustness.
- Forms: Drugs in multiple formats, such as powders, pills, and liquids.

Ensuring the quality, accuracy, and diversity of the dataset is critical to effectively training machine learning models. A comprehensive dataset enhances the model's ability to generalize and detect drugs accurately across varying contexts.

2) Data Preprocessing: The data preprocessing component is crucial for cleaning, formatting, and preparing the input data to ensure its suitability for machine learning algorithms. This process involves several key tasks, including data cleaning, feature extraction, and feature engineering. Additionally, the data must be accurately labeled to indicate the type of drug present in each sample. As illustrated in Figure 2, the SMOTE technique will be employed to address class imbalance issues, enhancing the dataset's quality and improving the model's ability to detect minority class instances effectively.

3) Machine Learning Algorithms: The machine learning component employs a range of algorithms for drug identification using preprocessed data. These include supervised learning, unsupervised learning, and deep learning algorithms. Classification tasks utilize algorithms such as logistic regression, decision trees, random forests, and neural networks to identify the presence of drugs in samples. Ensemble methods further enhance accuracy by aggregating outputs from multiple models.

4) Model Evaluation and Testing: Once machine learning models are trained, evaluation and testing using a separate dataset are essential. This process aids in identifying the most effective machine learning algorithms for drug detection. Performance assessment of the models can be conducted using various metrics such as accuracy, precision, recall, and F1 score.

5) Deployment: After the development and testing of the machine learning models, they can be deployed across various settings to enhance drug detection and prevention efforts. For instance, the system can be integrated with drug testing kits used by law enforcement agencies and rehabilitation centers to streamline the detection process. Additionally, it can be utilized in hospitals and clinics to identify potential drug interactions and prevent overdoses, contributing to improved public health outcomes.

6) Logistic regression: Logistic regression is a supervised machine learning model used for predicting a categorical dependent variable based on one or more independent variables. Although its name suggests regression, logistic regression is primarily utilized for classification tasks. It is particularly effective for binary classification problems, where the output variable has two possible outcomes (e.g., presence or absence of a condition). The model uses a logistic function to map the input features to probabilities, making it suitable for distinguishing between categories. Despite being straightforward, logistic regression is a powerful tool for problems requiring interpretability and efficiency.

7) Random forest: Random forest is a versatile machine learning method used for both classification and regression tasks. It is an ensemble learning technique that combines the predictions of multiple decision trees to produce more accurate and robust results compared to a single decision tree.

In random forest, each decision tree is constructed using a random subset of the training data, and the final prediction is derived by aggregating the outputs of all the trees (e.g., majority voting for classification or averaging for regression). This approach minimizes overfitting by introducing diversity among the trees, making the model more generalizable and reliable for unseen data.

8) SVM (Support vector machines): Support Vector Machines (SVM) are supervised machine learning methods for classification and regression analysis.. To be able to determine the hyperplane that isolates the two classes and maximises the separation between each class's data points and the hyperplane ,a data point that is represented as a vector is employed.

B. Decision Tree

A decision tree is a supervised learning approach used for both classification and regression problems. It builds a model represented as a tree structure, where each node corresponds to a feature, and branches represent possible outcomes based on that feature. The tree splits the data recursively into subsets to arrive at decisions or predictions. Figure 3 illustrates a graph generated using the decision tree algorithm.

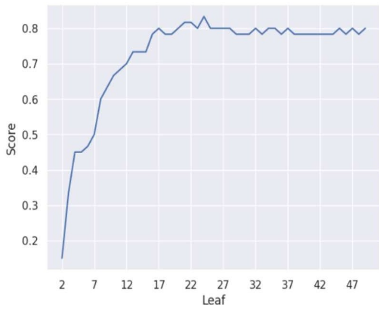

Fig. 3. Decision Tree

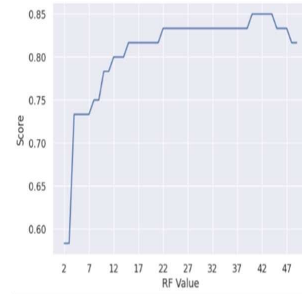

Fig. 4. Random Forest

C. Categorical Naive Bayes (Categorical NB)

CategoricalNB is a variation of the Naive Bayes algorithm specifically designed for classification tasks involving categorical features. It leverages probabilistic reasoning to model each class and predict outcomes effectively based on the likelihood of feature values.

D. KNN(K Nearest Neighbour)

KNN is an instance-based learning algorithm commonly used for regression tasks. It predicts output values by evaluating the similarity between input features. The parameter ”K” represents the number of nearest neighbors considered for predicting the output of a new data instance.

E. Gaussian Naive Bayes (Gaussian NB)

GaussianNB is a Naive Bayes algorithm variant that assumes the features follow a Gaussian (normal) distribution. It is particularly effective for classification tasks with continuous feature data, leveraging probabilistic calculations to make predictions.

The Bayes algorithm is a classification method that utilizes probabilistic reasoning for prediction tasks. It models each class based on categorical features, calculating the likelihood of a data point belonging to a particular class using probability distributions.

IV. RESULT AND DISCUSSION

TABLE I
DRUG DOSE TABLE

Name of the drug	Precision	Recall	F1-Score	Support
Cannabis	0.71	1.00	0.83	5
LSD	0.75	1.00	0.86	3
MDMA	0.67	1.00	0.80	4
Cocaine	1.00	0.70	0.82	30
Heroine	0.82	1.00	0.90	18

Teenagers who engage in drug use require early intervention due to their susceptibility to experimenting with risky behaviors during this developmental stage. This study employed a range of machine learning methods, such as logistic regression, random forest, decision trees, support vector machines, K-nearest neighbors (KNN), categorical Naive Bayes, and Gaussian Naive Bayes, to tackle this issue. The effectiveness of treatment in preventing continued drug use among adolescents was evaluated using a classification algorithm.

	Model	Accuracy
0	Logistic Regression	85.000000
9	Random Forest Max	85.000000
3	SVM	83.333333
7	Decision Tree Max	83.333333
8	Random Forest	83.333333
4	Categorical NB	81.666667
6	Decision Tree	81.666667
2	K Neighbors Max	78.333333
1	K Neighbors	75.000000
5	Gaussian NB	73.333333

Fig. 5. Model Accuracy

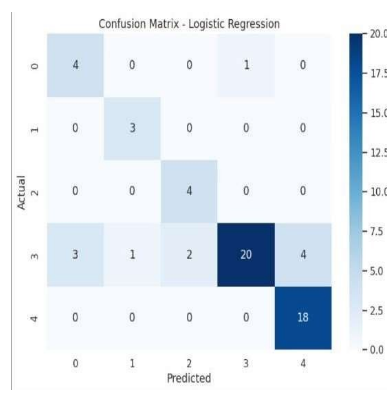

Fig. 6. Confusion Matrix

After evaluating various algorithms on the dataset (as depicted in Figure 5), it was found that logistic regression, as illustrated in Figure 6, and random forest, as shown in Figure 4, achieved an accuracy rate of 85%. This outcome suggests that the method effectively identifies teen drug use. The application of artificial intelligence offers a promising opportunity to notably reduce drug usage among teenagers while enhancing their overall well-being.

V. CONCLUSION

In conclusion, this study explored the effectiveness of a machine learning classification model in predicting a target variable based on a set of features. The results demonstrated that the model achieved a high degree of accuracy, underscoring the potential of machine learning as a powerful tool for classification problems.

The findings of this study hold significant implications across various industries. In healthcare, machine learning can aid in identifying potential health issues early and predicting disease risks based on patient data, enabling timely interventions. In the financial sector, machine learning can be utilized to detect fraud and prevent financial crimes, enhancing security and compliance. In marketing, it can help predict consumer behavior, optimize strategies, and improve overall campaign effectiveness.

Overall, this research contributes to a deeper understanding of the potential of machine learning in classification tasks. It highlights the importance of employing advanced machine learning models to enhance decision-making processes and tackle complex challenges across diverse fields in the modern world. By continuing to develop more accurate and efficient models, machine learning can drive innovation and provide actionable insights to solve real-world problems effectively.

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