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Nicotine Use and Psychotropic Drug Orientation: Machine Learning-Based Early Intervention Methods

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Abstract

Nicotine consumption is a condition that negatively affects the health of millions of people worldwide each year and leads to severe addiction problems. This study aims to develop and evaluate a machine-learning model for predicting nicotine consumption patterns and quitting times. By analyzing factors influencing nicotine use, the research seeks to identify the most appropriate time intervals for intervention before the transition to addiction. Moreover, the interactions between nicotine addiction and the use of psychotropic narcotic drugs have been examined in depth. The results show that nicotine addiction increases the risk of developing narcotic drug dependence, highlighting the importance of early intervention strategies. In analyses using machine learning models, the highest performance was achieved by Support Vector Machines with an accuracy of 94.07% and an F1 score of 91.24%. These findings have the potential to assist healthcare professionals in managing prescription processes more consciously and preventing addictive behaviors. The study provides significant scientific and practical contributions to better understanding the connections between nicotine and narcotic addictions and developing more effective intervention strategies in healthcare services.

Key words: Nicotine dependence, machine learning, psychotropic drugs, drug discovery, addiction prediction

1. Introduction

State Nicotine use remains a significant public health issue on a global scale. According to the World Health Organization, tobacco products cause millions of deaths each year. This highlights the need to intensify efforts to prevent and manage nicotine addiction [1]. Similarly, while psychotropic drugs play a crucial role in the treatment of mental health disorders, the misuse of these drugs can lead to serious health problems. Investigating the potential relationships between nicotine use and psychotropic drug use has emerged as a critical area of research in addiction science [2].

Nicotine addiction, arising from the use of tobacco and tobacco products, is considered a key stepping stone to the use of other addictive substances. While the treatment of nicotine addiction can be challenging, successful treatment can prevent the development of different types of addictions. In this context, understanding nicotine use and developing effective intervention

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strategies is paramount for public health. Early intervention can play a critical role in preventing nicotine addiction and improving treatment processes [2]. Globally, changes in approaches to psychiatry and psychiatric treatments, the use of new-generation drugs, the adverse side effects associated with these medications, and the increasing prevalence of depression, anxiety disorders, and substance abuse have all contributed to the growing use of psychotropic drugs. While these drugs are intended for therapeutic purposes, their abuse has also become a concern. It is difficult to predict the effects of drug misuse on individuals, and dangerous consequences often arise. To fully understand the drug problem, it is essential to comprehend the characteristics of narcotic substances, their effects on individuals, and their broader social impacts [3].

Drug addiction is a condition characterized by the interaction between the central nervous system and a psychotropic drug, which stimulates or depresses functions such as perception, mood, behavior, mental, and sometimes motor functions. This results in a psychic and occasionally somatic dependence, where individuals exhibit a craving or hunger for the drug, leading to its periodic or continuous use [4]. Addiction poses significant harm not only to the individual's health but also to their surroundings and society at large. The individual's health may be compromised by the drug's toxic effects or accidental overdose, while the indirect consequences of these effects can also be harmful. The neurological effects of substance addiction and the associated involvement in criminal activities have become one of today's primary concerns. Additionally, the increased supply of narcotic drugs is causing social security issues. To address this problem, it is necessary to profile individuals involved in drug-related crimes. Such profiling can help improve efforts to reduce supply, prevent drug use, and enhance education, as well as treatment and rehabilitation activities [3]. The connection between nicotine use and other psychoactive drugs reveals addiction tendencies. Research shows that individuals who use nicotine are highly likely to try other substances. This phenomenon is referred to as "polysubstance use," where nicotine serves as a gateway substance, often used alongside others. Furthermore, genetic structures and biological factors influence substance use. The effects on the dopamine system, in particular, determine individuals' inclination toward nicotine and other stimulants [5].

Psychological and social factors also play a significant role in the relationship between nicotine and other psychoactive drug use. Psychological conditions such as stress, anxiety, and depression can trigger the use of nicotine and other substances. In addition, social environments and peer pressure, especially among teenagers and young adults, tend to increase substance use. A comprehensive examination of such factors is critical in developing effective health interventions and policies, which can be used to shape public health strategies [6]. Scientific studies on the application of machine learning in the health sector demonstrate the applicability and effectiveness of these technologies in addressing health-related challenges both theoretically and practically. Particularly in areas like nicotine use, which has a direct impact on public health, the use of machine learning algorithms is considered an important area of research. These algorithms offer the potential for personalized treatment and intervention in health promotion and behavior change efforts, thereby improving individuals' participation and adherence to treatment. Additionally, machine learning facilitates the early diagnosis of diseases, health monitoring, and prediction of treatment outcomes by analyzing information from large and complex datasets. These features are expected to enhance the management of modifiable lifestyle factors and contribute to more effective healthcare management [7]. Machine learning enables the development of personalized health interventions by analyzing individuals' behaviors and habits in detail. This is especially critical for conditions like nicotine addiction, where individual differences can affect treatment success. Moreover, machine learning algorithms' time and cost efficiency allows for quick and efficient large-scale data analysis [7], contributing to the more efficient operation of healthcare systems. By optimizing time and resource usage, machine learning improves overall health management. These multifaceted capabilities make machine learning an indispensable element of modern healthcare applications. The use of machine learning algorithms is expected to significantly contribute to shaping health policies and increasing the effectiveness of early intervention programs. In this context, this study on nicotine use provides a valuable contribution to scientific knowledge and public health improvement [11].

This study presents a comprehensive data analysis aimed at better understanding nicotine use and its interactions with psychotropic drugs. The primary objective of the research is to determine the impact of nicotine consumption on psychotropic drug use and, based on this information, to develop effective intervention strategies. Machine learning methods are applied to predict nicotine consumption, enabling the early detection of individuals' risk of drug use. This approach aims to assist healthcare professionals in developing early intervention and personalized treatment strategies. Furthermore, the study explores the use of machine learning methods to predict the consumption of nicotine and other psychoactive drugs. By utilizing this model, healthcare professionals can reduce the risks of incorrect drug prescriptions and addiction, thereby supporting safer and more effective medication management. Additionally, it provides a practical tool for pharmacists and other healthcare professionals in risk assessment and patient management processes, aiming to deepen the scientific understanding of preventing and managing psychoactive drug use.

2. Materials and Method

2.1. Dataset

This study used a dataset containing information on 1,885 participants obtained from the UCI open-source website. This dataset was extensively evaluated to predict factors affecting nicotine use. The anonymized dataset includes participants' nicotine consumption status and demographic information. Variables such as age, gender, education level, and socioeconomic status are included among the participants [8]. All input features were initially categorical and later numerically encoded. As a result of the encoding process, the values of all input features were converted into real numbers.

Feature	**Description**	**Data Type**
Age	Age of the participant	Numerical
Gender	Gender of the participant	Categorical
Education	Education level	Ordinal
Country	Country of residence	Categorical
Ethnicity	Ethnic background	Categorical
Nicotine	Nicotine use	Ordinal

Cannabis	Cannabis use	Ordinal
Alcohol	Alcohol consumption	Ordinal
Caffeine	Caffeine consumption	Ordinal
Amphetamine	Amphetamine use	Ordinal
Cocaine	Cocaine use	Ordinal
Heroin	Heroin use	Ordinal
Methamphetamine	Methamphetamine use	Ordinal

Table 1*:* Dataset Description

This research was conducted using a large dataset related to various sociodemographic characteristics, consumption habits, and the use of different drugs. The dataset includes basic demographic information such as participants' age, gender, education level, country of residence, and ethnic background. However, in this study, specific behavioral data such as nicotine, cannabis, alcohol, caffeine, amphetamine, cocaine, heroin, and methamphetamine use were mainly included in the analysis. These features were selected to provide an in-depth examination of the participants' substance use habits. Features not included in the study were excluded to maintain a clear focus, allowing the model to produce more targeted and refined results.

The participants' age distribution ranges from 18 to 65 years, with an average age of 35. This age range demonstrates that the study covers a broad age group and represents various age cohorts. The gender distribution is 40% male and 60% female, indicating a balanced gender distribution within the participant population, which enhances the study's representativeness in terms of gender. Regarding education level, 30% of the participants have a high school education, 50% have a university degree, and 20% have completed postgraduate education. This distribution reflects diversity in education level and shows that the participants come from different educational backgrounds. These demographic characteristics are critical for understanding the sample structure and assessing the generalizability of the study's results.

2.2. Data Preprocessing

The dataset used in this study contains various features, including information on demographic and substance use. While demographic features such as age, gender, education level, country, and ethnicity are present in the dataset, they were not used in the analysis due to their low capacity to directly predict nicotine use. These demographic variables, which are numerical and categorical, were excluded from the model as they were considered to affect the accuracy and generalization ability of the model negatively.

The features included in the analysis focus on the use of nicotine and other substances. The usage levels of substances such as cannabis, alcohol, caffeine, amphetamines, cocaine, heroin, and methamphetamines are ordinal data types, indicating how often and to what extent individuals use these substances. Nicotine use was identified as the primary focus of the study, and its relationship with the usage levels of other substances was evaluated. The inclusion of all features related to substance use in the analysis was done to improve the model's performance and achieve more accurate predictions of nicotine use. By excluding demographic variables, the focus was shifted to highlight the effects of substance use better.

Feature	Description	Value
Total Participants	The number of participants initially recruited	1,885
Participants Analyzed	Number of participants whose data was analyzed	1,550
Exclusion Criteria	Criteria for excluding participants from the analysis	Missing data, withdrawal of consent
Inclusion Criteria	Criteria for participation in the study	Above 18 years old, informed consent
Study Duration	Total duration of the study	12 months
Age Range	The age range of the participants	18-65 years
Mean Age	The mean age of the participants	35 years
Gender Distribution	Gender distribution of the participants	60% female, 40% male

Table 2: Participant Characteristics

Initially, a total of 1,885 participants were recruited, and 1,550 of these participants were evaluated for analysis. The inclusion and exclusion criteria for participants in the analysis were based on specific measures. Situations such as missing data or withdrawal of consent led to the exclusion of participants from the study. The inclusion criteria included requirements such as being over 18 years old and providing informed consent. The study duration was set at 12 months, with participants' ages ranging from 18 to 65 years. The mean age was calculated to be 35 years, demonstrating that the study covered a wide age range. The gender distribution was determined to be 60% female and 40% male, indicating that the study ensured gender representation. These demographic details are essential for assessing the study's generalizability and the results' applicability to different groups. All 1,885 participants initially recruited were considered the analysis's starting point. However, after the data cleaning processes, the number of participants was reduced. Following data cleaning steps, such as removing missing data and outliers, the number of participants available for analysis dropped to 1,700, representing 90.19% of the initial total. Subsequently, applying inclusion criteria further reduced the number of participants to only those with specific characteristics. For example, only participants who used nicotine were considered, which reduced the number of participants analyzed to 1,550, corresponding to 82.23% of the initial total. This process was critical for enhancing the reliability and accuracy of the study, helping to make the dataset more focused and suitable for relevant analyses. Such a filtering process is a commonly used method to increase the validity of study results.

During the data analysis process, various data processing steps are applied to improve data quality and ensure the reliability of the models. First, a missing data imputation method is used to fill in the missing values in the dataset, using the median for continuous variables and the mode for categorical variables. This step is crucial for filling the gaps in the dataset and ensuring the smooth progress of the analysis process. Second, an outlier removal process is performed. In this step, outliers detected using the IQR (Interquartile Range) method are removed from the dataset. Cleaning outliers is a critical step to reduce the impact of unusual values that may distort the overall distribution of the dataset [17]. Finally, an inconsistent data correction process is applied. In this process, illogical or inconsistent data entries are corrected or removed from the dataset in consultation with domain experts. Consistency checks are essential in increasing accuracy and reliability during the data analysis. These data processing steps are meticulously carried out to improve the accuracy and generalizability of the model.

The analytical depth of the study is highlighted by the machine learning models used and the performance evaluation metrics of these models. Four models (Logistic Regression, Ridge Classifier, Support Vector Machines, and Random Forest Classifier) were used to predict nicotine use. Performance metrics such as accuracy and F1 score for each model were compared to determine how effective the models were and which model best predicted nicotine use. This process reveals the models' strengths and limitations and provides insights into how complex behavioral patterns such as nicotine use can be analyzed using machine learning techniques.

2.3. Machine Learning Methods

This study applied four machine learning methods—Logistic Regression, Random Forest, Support Vector Machines (SVM), and Ridge Classifier—to predict nicotine use. Logistic Regression is commonly used as a basic approach for binary classification problems. Random Forest aims to improve model accuracy by combining multiple decision trees. Support Vector Machines (SVM) provide effective classification by identifying the best boundaries that separate data points. By adding a regularization term, the Ridge Classifier prevents the model from overfitting and ensures stability, especially in datasets with multicollinearity issues. These methods allow for evaluating the performance of various algorithms and selecting the most suitable model [9].

Logistic regression is a significant regression method often used in data analysis to explain the relationship between a class attribute and one or more features. In this method, the class attribute is typically discrete and can take two or more possible values. Logistic regression is one of the most widely used models for solving such classification problems, especially in cases where the dependent variable is categorical. Therefore, the logistic regression model is widely applied to obtain accurate and reliable results in classification problems [9].

The Random Forest method is an ensemble algorithm of decision trees grown on bootstrap samples of the training dataset, with random feature selection during the tree-building process. In this method, predictions are made by aggregating the predictions from each tree. Since a Random Forest is an ensemble of multiple decision trees, it usually performs better than classifiers based on a single tree. Random Forest becomes a good choice, particularly in handling large-scale data. However, when imbalanced training datasets are used, the performance of the Random Forest method may degrade. While its tendency to minimize the overall error rate can lead to higher accuracy, it may sometimes weaken the ability to correctly predict the minority class [10].

Support Vector Machines (SVM) is a robust machine learning algorithm widely used in classification and regression analysis. SVM aims to find the hyperplane that best separates the data and defines boundaries that maximize this separation. While effective in linearly separable data, SVM can also classify non-linear datasets using kernel functions. These kernel functions transform the data into a higher-dimensional space, making it easier to separate the data in that space. One of the advantages of SVM is that it uses only data points known as support vectors to determine decision boundaries. This enhances the model's generalization ability and allows it to perform well even with smaller datasets. However, it's important to note that SVM's training time can be long, and the computational cost can be high in imbalanced or very large datasets. Despite these considerations, SVM is considered a reliable and effective method in high-dimensional datasets and complex classification problems [11].

The Ridge Classifier is a machine learning algorithm, a variation of logistic regression, that aims to improve model performance in classification problems by adding regularization. This method adds an L2 regularization term to control the model's complexity and reduce the risk of overfitting. The Ridge Classifier performs effectively in multicollinear datasets because the regularization term enhances the model’s stability when there is a high correlation among features. Additionally, the Ridge Classifier improves generalization ability in small datasets or datasets with many features, providing more balanced and reliable predictions. However, one disadvantage of this method is that it shrinks the parameters by considering all features, which may sometimes reduce interpretability. Ridge Classifier stands out as a robust classification tool, particularly when relationships between variables are complex, and the risk of overfitting is high [12].

2.4. Performance Metrics

In this study, four key metrics—F1 score, accuracy, precision, and recall—are used to evaluate the performance of classification models. The F1 score, by considering the balance between recall and precision, allows for a more accurate evaluation of classification performance, particularly in imbalanced datasets. The accuracy score, which measures the overall success rate of the model, is a metric widely used to compare different models. These two metrics are used together to evaluate the performance of various algorithms comprehensively and to determine the most suitable model.

Accuracy is one of the most common performance metrics used to measure the overall success rate of a classification model. This metric represents the ratio of correctly predicted instances to the total number of predictions made. While the accuracy score provides a quick insight into the model's overall performance, it also offers a general perspective on the correctness of predictions for each class. However, particularly in imbalanced datasets, it may not be sufficient as an evaluation metric, as it can mask errors in the minority class. In this study, accuracy is used to assess classification models' general performance and compare different algorithms alongside the F1 score for more detailed analysis [13]. The F1 score is an important metric used to evaluate the performance of classification models, especially in imbalanced datasets. This metric combines precision and recall, providing a general summary of classification performance. By considering the ratio of true positives to false positives and false negatives, the F1 score reveals how well the model predicts the minority class. Therefore, it serves as a reliable indicator for understanding the overall performance of the classification model, particularly in imbalanced data distributions. In our study, the F1 score is used to assess how accurately different models predict the minority and majority classes [14]. Precision is an essential metric that measures the ratio of true positive predictions to all positive predictions made by a classification model. In other words, it shows how many examples labeled as positive by the model are positive. A high precision value indicates that the model is selective in its positive predictions and makes fewer false positive predictions. Precision is critically important, especially in applications where false positives are costly, such as in healthcare with incorrect diagnoses. This study uses precision to evaluate the models' true positive rates, ensuring a more accurate understanding of overall performance [18] Recall, on the other hand, measures the ratio of true positive predictions to the total number of actual positive cases. This metric indicates how well the model can correctly predict all instances belonging to the positive class. A high recall value suggests that the model does not miss any examples from the positive class and can correctly identify all positives. Recall is significant in situations where missing a positive instance is costly, such as in disease diagnosis, where positive cases should not be overlooked. This study uses recall to assess how well the models predict the positive classes without missing any examples [19-20].

3. Results

This study provides new insights into the interactions between nicotine and psychotropic drug use, offering valuable information for health administrators, strategy experts, and planners. This information may play a critical role in combating nicotine addiction and promoting more responsible use of psychotropic drugs. Therefore, the findings are considered to have the potential to contribute to strategies aimed at protecting and improving public health [15].

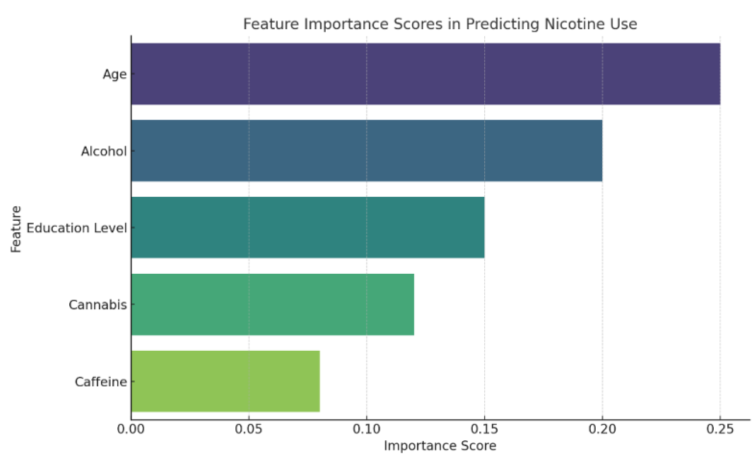

Figure 1: Feature Importance Scores in Predicting Nicotine Use

In the analysis conducted, the importance of the features used to predict nicotine use was evaluated. Feature importance scores reflect the predictive power attributed by the model to each feature, revealing which variables are more decisive in forecasting nicotine use. This analysis shows that factors such as age, alcohol consumption, and education level are critically important for the model in predicting nicotine use. In particular, the strong correlation between age and alcohol consumption with nicotine use suggests that these variables provide significant insights into understanding smoking behavior. Utilizing such information can contribute to designing more effective policies and programs to reduce smoking.

Model	**Accuracy**	**F1 Score**	**Precision**	**Recall**
Logistic Regression	92.52%	89.19%	90.00%	88.00%
Ridge Classifier	92.10%	88.91%	87.00%	83.00%
Support Vector Machines	94.07%	91.24%	92.00%	90.00%
Random Forest Classifier	93.65%	90.54%	89.00%	87.00%

Table 3: Model Performances for Nicotine Users

In Table 3, the performance of different machine learning models was comprehensively evaluated using the metrics of Accuracy, F1-score, Precision and Recall.The logistic regression model demonstrated strong performance in binary classification problems, with an accuracy of 92.52%, an F1 score of 89.19%, a Precision of 90.00%, and a Recall of 88.00%. Similarly, the Ridge classifier model achieved an accuracy of 92.10%, an F1 score of 88.91%, a Precision of 87.00%, and a Recall of 83.00%, showing a performance close to logistic regression, albeit with a slight decrease in accuracy. The random forest model, with an accuracy of 93.65%, an F1 score of 90.54%, a Precision of 89.00%, and a Recall of 87.00%, effectively modeled the variability in the dataset and provided high generalization capability, demonstrating strong performance.

Among all the models, the Support Vector Machines (SVM) showed the highest performance with an accuracy of 94.07%, an F1 score of 91.24%, a Precision of 92.00%, and a Recall of 90.00%. The ability of SVM to effectively model non-linear relationships was the primary reason for this superior performance. The findings indicate that the SVM and random forest models are more suitable and effective for the analyzed dataset than other models. The SVM model's accuracy of 94% in predicting nicotine consumption demonstrates its effectiveness. This high accuracy shows that the model can reliably classify different cases in the dataset and, thus, may play a critical role in early diagnosis and intervention strategies. Moreover, the F1 score, measured at 92%, indicates that the model offers balanced performance in both precision and recall. This allows healthcare professionals to confidently use the SVM model in scenarios where minimizing false positives and negatives is crucial. The high F1 score provides a strategic advantage by ensuring the accurate identification of individuals at risk for nicotine addiction, facilitating early intervention, improving health outcomes, and reducing healthcare costs. These scores show that the model can effectively detect nicotine consumption with a low rate of false positive and false pessimistic predictions. This outcome suggests that the increase in nicotine consumption parallels an increase in psychotropic drug use. The analysis of demographic factors further reveals that young adults and individuals with lower educational levels have higher rates of nicotine consumption. These findings underscore the connection between nicotine use and socioeconomic and demographic factors [16].

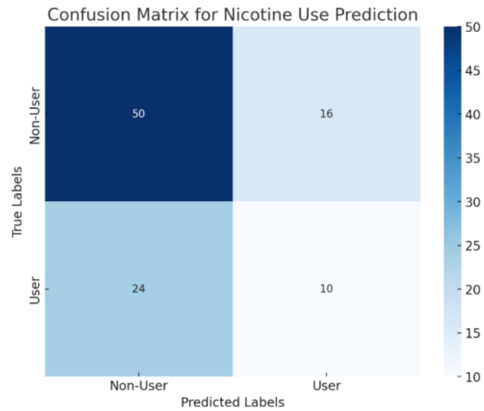

Figure 2: Confusion Matrix for Nicotine Consumption Prediction

The confusion matrix resulting from the analysis is presented in Figure 2. This confusion matrix evaluates the model's performance in predicting nicotine consumption. The graph visualizes the alignment of the model's predictions with actual labels while also revealing the classification errors made by the model. As observed, the rate at which individuals who consume nicotine are incorrectly classified as "non-consumers" indicates an area where the model needs improvement. Furthermore, the confusion matrix shown here does not reflect the dataset of approximately 1,885 records; rather, it represents the test results from a smaller subset of the model. The matrix includes only 100 data points, which is a preliminary analysis to assess how the model might perform with a larger dataset. This matrix evaluates the agreement between actual and predicted labels visualized across four cells. The top left cell represents the instances where non-consumers were correctly predicted as "non-consumers," with 50 correct predictions in this category. The top suitable cell represents the cases where non-consumers were incorrectly predicted as "users," with 16 incorrect predictions recorded here. The bottom left cell represents the instances where nicotine users were incorrectly classified as "non-users," with 24 incorrect predictions in this group. Lastly, the bottom suitable cell shows the cases where nicotine users were correctly predicted as "users," with ten correct predictions recorded in this category. This confusion matrix is a critical tool for evaluating the model's overall performance and understanding instances of misclassification. Based on the matrix analysis, it is evident that there are some limitations in the model's ability to predict nicotine consumption, and therefore areas for improvement. Specifically, the rate of incorrect predictions where users are classified as "non-users" points to a significant area where the model needs enhancement.

One of the primary limitations of this study is that the dataset used represents a specific population, which may make it challenging to generalize the results to populations with different demographic structures. The limited scope and diversity of the dataset may also negatively impact the model's ability to generalize across all scenarios of nicotine consumption. Therefore, future studies aim to improve the generalizability of the findings by using more extensive and more diverse datasets that encompass various demographic characteristics. Additionally, employing qualitative methodologies to explore potential causal relationships between nicotine and psychotropic drug use may contribute to a better understanding of the underlying mechanisms of these relationships.

4. Conclusions

This study thoroughly examines the relationships between nicotine use and the consumption of potentially addictive psychotropic drugs. The analysis, conducted on a dataset spanning a wide demographic range, reveals the connections between nicotine use and various health and psychological factors. Notably, the use of machine learning algorithms, particularly Support Vector Machines (SVM), has shown the highest performance in predicting nicotine use, achieving an accuracy of 94.07%, an F1 score of 91.24%, Precision of 92.00%, and Recall of 90.00%. Among other models, Logistic Regression performed with an accuracy of 92.52%, an F1 score of 89.19%, Precision of 90.00%, and Recall of 88.00%, while the Ridge Classifier achieved an accuracy of 92.10%, an F1 score of 88.91%, Precision of 87.00%, and Recall of 83.00%. The Random Forest Classifier also demonstrated strong performance, with an accuracy of 93.65%, an F1 score of 90.54%, a Precision of 89.00%, and a Recall of 87.00%.

These findings highlight the potential of machine learning algorithms in predicting nicotine use and offer insights into how the obtained data could inform health policies and early intervention programs. By leveraging the precision and recall metrics alongside the overall accuracy and F1 scores, the study underscores the balance between minimizing false positives and false negatives, which is critical in healthcare settings. This comprehensive approach provides scientific and societal contributions, offering potential strategies for improving public health outcomes through targeted interventions.The findings of this study provide significant insights into the early diagnosis and management of nicotine use. The model developed through the SVM algorithm has successfully predicted both the initiation time and frequency of nicotine consumption. This model enables healthcare professionals and strategy developers to make more informed and effective decisions regarding the prevention and management of addiction. Additionally, the detailed analyses of nicotine and psychotropic drug use offer valuable contributions toward reducing the misuse of these substances and improving overall health levels.

The study’s findings, particularly in the context of prescription processes, support and enhance decision-making for healthcare professionals. Understanding the use of nicotine and other addictive substances helps reduce prescription errors and aids in developing safer and more effective medication strategies for patients. This represents a significant advancement in pharmaceutical practices and medication management. The results of our research can serve as a crucial resource in shaping health policies and designing programs aimed at reducing nicotine use. As effective risk assessment tools, machine learning models allow healthcare services to develop proactive and preventive approaches. These models can contribute to creating more targeted and efficient strategies for the prevention and control of nicotine use.In conclusion, this research provides valuable insights for developing strategic approaches to public health. The importance of multidisciplinary approaches and community-based interventions in addressing nicotine addiction and related health problems is once again emphasized. Future studies are expected to extend these findings to broader audiences, further improving public health. This research offers significant scientific and practical advancements in understanding and managing nicotine use, providing a solid foundation for future studies.

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