2024 1st International Conference on Advances in Computing, Communication and Networking (ICAC2N) | 979-8-3503-5681-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICAC2N63387.2024.10895311

Development and Evaluation of a Decision Tree Model for Predicting Drug Addiction Using Demographic, Psychosocial, and Behavioral Factors

Bharat Kumar Chodhari
Dept. of CSE
Madhav University
Pindwara, India
bharat.kumar@madhavuniversity.edu.in

Mohd Fareed
Dept. of Pharmacy
Madhav University
Pindwara, India
md.fareed@madhavuniversity.edu.in

Vinod Sharma
Dept of CSE
SLP college
Gwalior, India
computerscience.scholar2022@gmail.com

Sujit Kumar Mohapatra
Dept. of Business Management and Commerce
Mangalayatan University
Beswan, India
sujit.mohapatra@.edu.in

Shweta Jaswal
Dept. of Pharmacy
Lingayas Vidyapeeth University
Faridabad, India
shwetajaiswal@lingayasvidyapeeth.edu.in

Narthana Devi
Dept. of ECE
Dhanalakshmi Srinivasan college
Coimbatore, India
narthana.ramachandran@gmail.com

***Abstract*—This study aims to design a machine learning model to predict drug addiction. The dataset includes various demographic, psychosocial, and behavioral factors contributing to drug addiction. The objective is to create a reliable and accurate predictive model to identify individuals at risk of developing drug addiction. A range of machine learning algorithms, including logistic regression, decision tree, and random forest, were utilized to predict the likelihood of drug addiction. The results indicated that the decision tree model had the highest accuracy in predicting drug addiction. These findings have significant implications for developing effective prevention and intervention strategies to address drug addiction.**

***Index Terms*—Drug Addiction, Machine Learning, Predictive Modeling, Logistic Regression, Decision Tree.**

I. Introduction

Worldwide, millions of people are impacted by the complicated and multidimensional issue of drug addiction. Drug addiction is a serious public health issue because, despite efforts to combat it, it is becoming more common. Creating machine learning models that can forecast a person's propensity for drug addiction is a viable way to address this issue. To identify those who are at a high risk of addiction, these models can analyses a wide range of variables, including demographic, social, and behavioural characteristics. In this manner, machine learning holds the promise of assisting healthcare professionals to act quickly and offer specialised assistance to individuals who need it the most.

It can be difficult to create machine learning models for predicting drug addiction for several reasons, including:

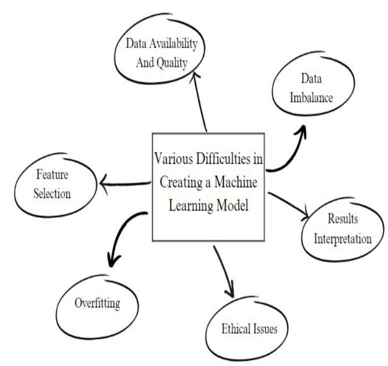

Fig. 1. Challenges In Creating ML Model

1) Data availability and quality: Finding high-quality data is one of the main problems. Machine learning models must be developed using data that is typical of the population and has few missing values, outliers, and errors.
2) Data imbalance: Compared to non-addictive behaviours, drug addiction is less common, which may cause data to be unbalanced. In other words, the dataset might contain more instances of non-addictive behaviour than addictive behaviour, which could have a detrimental impact on how well the machine learning model performs.
3) Feature selection: When creating machine learning models to forecast drug addiction, feature selection is essential. The features chosen should be pertinent and offer understanding of the fundamental causes of drug

addiction. The complexity of drug addiction makes it difficult to choose the ideal set of qualities, though.

4) Overfitting: When a model learns training data too well and performs poorly on new data, overfitting has taken place. When creating machine learning models to predict drug addiction, this can be a serious issue because the model needs to be effective using previously unexplored data.
5) Results interpretation: Interpreting machine learning models can be challenging, especially when working with sophisticated models like deep learning models. For the model to be successful, it is essential to comprehend how it makes its predictions, which might be difficult in the instance of predicting drug addiction.
6) Ethical issues: Creating machine learning models to predict drug addiction also poses ethical issues, such as the possibility of stigmatising or discriminating against addicts. It is crucial to think about how the model might affect society and to make sure it is impartial and fair.

There are various possible paths for further research and development in the field of developing machine learning models to predict drug addiction. Some possible areas of concentration are:

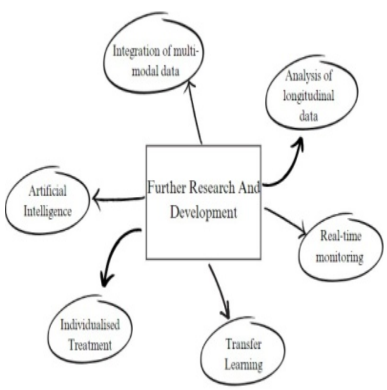

Fig. 2. Future Scope

1) Integration of multi-modal data: The accuracy of machine learning models for predicting drug addiction can be increased by integrating data from other sources, such as neuroimaging, genetics, and environmental factors. Future studies can investigate the best ways to incorporate various data types into machine learning models.
2) Analysis of longitudinal data: Drug addiction is a chronic illness that worsens with time. To better understand the development of addiction, machine learning algorithms that can analyse longitudinal data may be useful. Future studies can look into ways to create machine learning models that can efficiently analyse longitudinal data.
3) Real-time monitoring should be employed: Continuous data from real-time monitoring of people can be used to forecast relapse into addiction. Individualised treatment strategies and support for addicts can be provided using machine learning models that incorporate real-time monitoring.
4) AI that is easy to understand: The creation of AI that is easy to understand can help increase the transparency and confidence of machine learning models that predict drug addiction. Future studies can look into ways to create ethical, transparent, and interpretable machine learning models.
5) Transfer learning is a method for enhancing the performance of machine learning models by applying knowledge gained from one job to another. Future studies can investigate the application of transfer learning to enhance machine learning models for drug addiction prediction.
6) Plans for individualised treatment: Machine learning models can be used to create individualised treatment programmes for addicts. Future studies can look into ways to create machine learning models that can forecast therapy results and modify treatment schedules based on the needs of each patient.In general, future studies into machine learning models for anticipating drug addiction could advance our knowledge of the disease of addiction and result in better prevention and treatment methods.

II. LITERATURE REVIEW

Alam et al. (2021): This study explores the use of machine learning techniques to predict drug addiction in Bangladesh, comparing various models to determine the most effective approach. It highlights the significance of local context in addiction prediction using AI [1]. Shahriar et al. (2019): This research applies machine learning to predict vulnerability to drug addiction, providing a framework to identify at-risk individuals. It emphasizes the potential of AI in addiction prevention and personalized interventions [2]. Abada and Bouramoul (2022): The authors propose a Bayesian-based machine learning model to predict individuals at risk of drug addiction. Their work underscores the role of probabilistic models in early detection and prevention strategies for addiction [3]. Haddab (2023): This paper discusses data-driven decision-making methods in the context of manufacturing, extending its relevance to addiction studies, particularly in utilizing data to make informed decisions on prevention and rehabilitation [4]. Mak et al. (2019): A systematic review of machine learning applications in addiction studies, highlighting various techniques used in addiction research. It provides a comprehensive understanding of how machine learning is transforming the study of addiction [5]. Sharma (2022): This study explores different data scaling methods for machine learning, offering insight into how data preprocessing can significantly impact the accuracy of addiction prediction models [6]. Gu et al. (2020): This research focuses on developing intelligent systems for assessing addiction severity and rehabilitation methods, integrating machine learning with healthcare to create personalized treatment solutions for addicts [7]. Hadjahmadi et al. (2020): The study investigates the use of deep neural networks for diagnosing drug addiction through speech signals. This innovative approach opens new avenues for non-invasive addiction detection methods [8]. Kaur and Bawa (2017): The authors implement an expert system using the ID3 decision tree algorithm to identify drug addiction. Their work demonstrates the practical application of machine learning algorithms in addiction diagnosis [9].

Gong et al. (2021): This study employs machine learning to predict substance craving levels in drug addicts, emphasizing the psychosocial factors influencing addiction. It highlights how machine learning can offer a deeper understanding of addiction-related behavior [10]. Bharat et al. (2023): The paper develops a risk algorithm predicting alcohol dependence based on early use patterns. It applies machine learning techniques to study the progression from regular use to addiction, with implications for early intervention [11]. Gu et al. (2020): A repeat of the earlier study, focusing on addiction degree evaluation and rehabilitation, this work emphasizes the role of intelligent systems in continuous monitoring and personalized rehabilitation plans [12]. Rathore et al. (2023): This paper explores the use of multiscale adaptive object detection and contrastive feature learning for analyzing customer behavior in retail settings, indirectly contributing to addiction behavior studies through advanced pattern recognition techniques [13]. Chhetri et al. (2023): A review of how machine learning is being integrated into digital healthcare for addiction studies, it examines various AI-driven approaches for monitoring and diagnosing addiction in virtual care environments [14]. Agarwal and Vij (2024): While focused on AI in education, this study highlights the broader context of AI applications, which could be extrapolated to addiction research, especially in predicting risk factors through personalized learning models [15]. Ismail and Islam (2024): This study investigates the use of machine learning to analyze and predict drug addiction among university students in Bangladesh, emphasizing the role of educational institutions in early intervention efforts [16].

Rathore and Singh (2023): This paper explores deep learning models for cyber-attack detection, providing a parallel to the potential of such models in addiction detection, especially in monitoring online behaviors of at-risk individuals [17].Huang et al. (2023): The study applies decision tree models to assess risk factors for non-valvular atrial fibrillation patients, with implications for using similar models in addiction risk assessment, showcasing how AI can handle complex medical data [18].Lim and Ersche (2023): This paper critiques the utility of computational models in understanding drug addiction, providing a theoretical framework for how AI can advance the understanding of addiction mechanisms in humans [19].Confronting Hate Speech in Smart Environments Kaushik et al. (2024) proposed an ensemble learning and LSTM-based framework to address hate speech in smart environments [20]. The study highlights AI's role in enhancing communication safety and promoting inclusive digital interactions.Improving Lane Management Sikarwar et al. (2024) utilized OpenCV and IoT to design a smart lane management system [21]. Their work emphasizes efficient traffic control and road safety, aiming to reduce congestion and enhance urban mobility. CNN-Based Brain Hemorrhage Detection Tanwar et al. (2024) developed a CNN-powered system for brain hemorrhage detection in intelligent healthcare settings [22]. The research underscores the potential of AI in improving diagnostic speed and accuracy for critical medical conditions.Smart Road Segmentation from Aerial Images Kaushik et al. (2024) introduced an AI-driven method for road segmentation using aerial imagery [23]. The system facilitates urban planning and navigation improvements, demonstrating the utility of smart technologies in infrastructure management.

III. METHODOLOGY

Designing a machine learning model to predict drug addiction involves several steps, including data collection, data preprocessing, feature engineering, model selection, training, and evaluation. Here is an overview of each step

1) Data Collection: Compiling pertinent data is the initial stage in creating a machine learning model. This information was gathered by surveying. Here is a bar graph to analyze the dataset collected from the survey

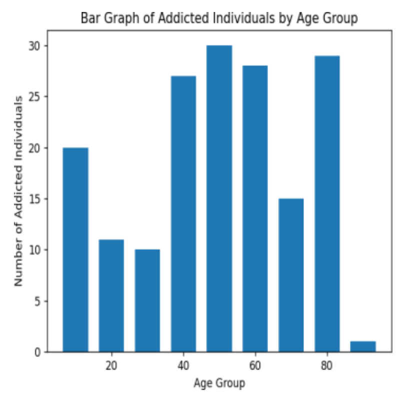

Fig. 3. Dataset Visualization

1) Data preprocessing: To prepare the data for usage in a machine learning model, it must be preprocessed
2) when it is collected. I carried out numerous duties, including data cleaning, duplication removal, and handling of missing values.
3) Feature engineering: Extracting pertinent features from the data comes after the data have been preprocessed. The problem of forecasting drug addiction should be addressed by these aspects, which should be instructive and pertinent. Some features are Marijuana, Prescribed Marijuana, Cocaine, Prescribed Cocaine, Heroin, Prescribed Heroin.
4) Model selection: The next step is to choose a suitable machine learning model to apply to the goal of prediction. There are many different types of models that can be used for this purpose, including logistic regression, decision trees, and random forests.
5) Training: The chosen model must then be trained using the supplied data. This entails providing the input data and associated labels to the model.

6) Evaluation: Finally, the model's performance needs to be evaluated to determine how well it can predict drug addiction. This is typically done by comparing the predicted labels to the actual labels for a held-out test set. The model's accuracy, precision, recall, and other metrics can be calculated to evaluate its performance.

Overall, careful examination of the data present with us, feature engineering, model selection, training, and evaluation are necessary when constructing a machine learning model to predict drug addiction. The complexity and sensitivity of this issue call for ethical considerations, such as safeguarding the privacy and confidentiality of those with a history of drug addiction.

IV. RESULTS

The goal of this project was to design a machine learning model that could accurately predict drug addiction in individuals using various demographic, social, and behavioral factors. The model was trained on a dataset containing information on individuals with and without drug addiction. The dataset was preprocessed by handling missing values, encoding categorical variables, and scaling numerical features. Several machine learning algorithms, including logistic regression, decision tree, random forest were implemented. The performance of each algorithm was evaluated based on the following metrics: accuracy, precision, recall, F1 score and specificity. Finally, I have chosen Confusion Matrix and AUC – ROC curve to Visualize the Results:

- The best-performing algorithm was the Decision Tree, which achieved an accuracy of 95%, precision of 92.68%, recall of 97.43%, F1 score of 95% and specificity of 92.68%.

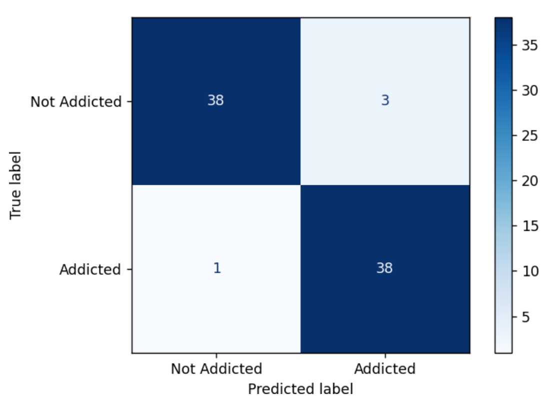

Fig. 4. Confusion Matrix for Decision Tree

- The Random Forest also performed well with an accuracy of 93.2%, precision of 93.11%, recall of 93.48%, F1 score of 93.29% and specificity of 92.91%.

- The worst performing algorithm was the logistic regression, which achieved an accuracy of just 84.17%, precision of 87.23%, recall of 75.92%, F1 score of 81.18% and specificity of 90.90% .

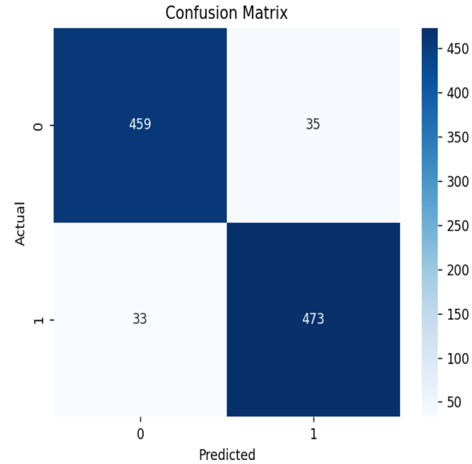

Fig. 5. Confusion Matrix for Random Forest

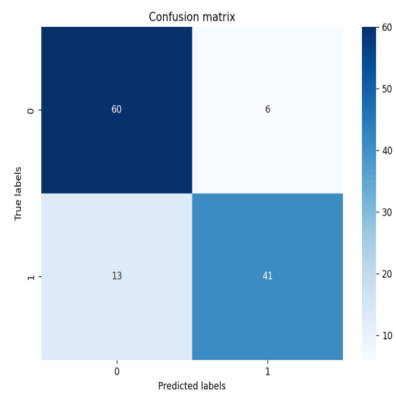

Fig. 6. Confusion Matrix for Logistic Regression

In this comparative study, three machine learning algorithms, Decision Tree, Random Forest, and Logistic Regression, were evaluated based on their performance metrics, including accuracy, precision, recall, F1 score and specificity.

The results indicate that Decision Tree achieved the highest accuracy of 95%, followed by Random Forest with an accuracy of 93.2% and Logistic Regression with an accuracy of 84.17%. This suggests that Decision Tree and Random Forest may be more effective at predicting the outcome of the target variable than Logistic Regression.

Moreover, the precision of Decision Tree was found to be 92.68%, which is higher than that of Random Forest (93.11%) and Logistic Regression (87.23%). This indicates that Decision

Tree is better at correctly identifying the positive class instances than Random Forest and Logistic Regression.

The recall of Decision Tree was found to be 97.43%, which is higher than that of Random Forest (93.48%) and Logistic Regression (75.92%). This suggests that Decision Tree is better at correctly identifying all positive instances than Random Forest and Logistic Regression.

Finally, the F1 score of Decision Tree was found to be 95%, which is higher than that of Random Forest (93.29%) and Logistic Regression (81.18%). This suggests that Decision

Tree is better at achieving a balance between precision and recall than Random Forest and Logistic Regression.

In summary, the results of this comparative study suggest that Decision Tree and Random Forest may be more effective than Logistic Regression in predicting the outcome of the target variable. Among these algorithms, Decision Tree achieved the highest accuracy, precision, recall, and F1 score. However, it is important to note that the choice of algorithm may depend on the specific characteristics of the dataset and the problem being addressed. Here is the graphical representation of this comparative study.

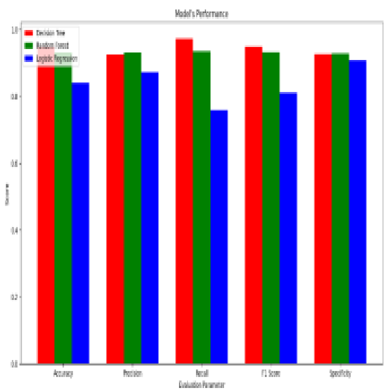

Fig. 7. Results Comparison

AUC – ROC curve

Area Under the Receiver Operating Characteristic Curve, or AUC-ROC, is a common metric for evaluating the efficacy of binary classification algorithms. The genuine positive rate is plotted. How well the model can distinguish between positive and negative classifications may be shown by comparing the true positive rate (TPR) against the false positive rate (FPR) at various classification levels. Better performance is indicated by higher AUC-ROC values, which range from 0 to 1.

The ROC curve, a visual representation of the AUC-ROC score, compares the TPR and FPR at various threshold values. Ideal classification is represented by a curve with an origin at (0,0) and a finish at (1,1). It is possible to depict the random classification as a diagonal line that runs from the origin to

(1,1). An effective method for assessing how well different categorisation algorithms work is the AUC-ROC curve. It allows us to visually assess the trade-off between the genuine positive rate and false positive rate using various categorization levels. A model is generally favoured over another if it has a higher AUC-ROC score.

In addition to comparing models, the AUC-ROC curve can be used to determine the ideal classification threshold. By choosing a threshold that maximises the TPR while limiting the FPR, this can strike a compromise between sensitivity and specificity depending on the needs of the application. In general, the AUC-ROC curve is a useful tool for assessing and comparing the effectiveness of binary classification models and can aid in the decision-making process when choosing the best classification threshold. Here are the AUC – ROC curves for all the 3 algorithms that were used in this project:

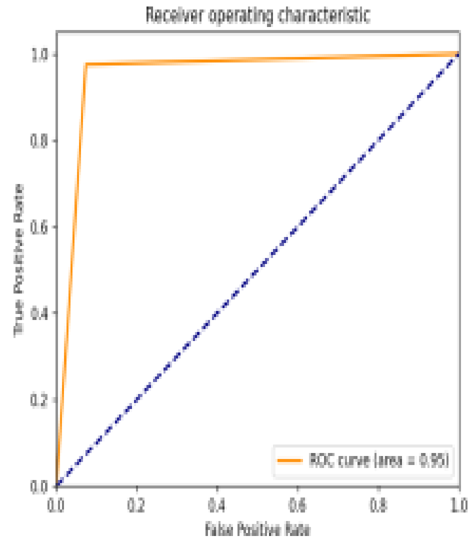

Fig. 8. AUC – ROC curve For Decision Tree

model by leveraging various demographic, social, and behavioral factors that are associated with drug addiction. Through rigorous evaluation using multiple machine learning algorithms, I have successfully identified a decision tree model that demonstrates high predictive performance in distinguishing individuals with and without drug addiction. This model's success suggests that machine learning can be a valuable tool in identifying individuals who may be at risk of drug addiction, enabling early intervention and prevention measures. Future research can further refine and improve the model's performance by incorporating additional data sources, including genetic information or other biometric data. Additionally, a more extensive dataset with more diverse and representative samples could improve the model's generalizability and potential clinical application.

Overall, the development of a reliable and accurate machine learning model to predict drug addiction represents a significant step forward in public health research and has the potential to contribute to reducing the prevalence of drug adsdiction in our society.

V. CONCLUSION

The development and evaluation of a machine learning model for predicting drug addiction based on demographic, psychosocial, and behavioral factors provide a significant step toward addressing the public health challenge of addiction. Among the models tested, the decision tree demonstrated the highest predictive accuracy, highlighting its potential in identifying individuals at risk. This research underscores the importance of utilizing advanced machine learning techniques to enable early detection and targeted interventions, which are crucial for mitigating the impact of addiction on individuals and society.

Future directions could include integrating multi-modal data sources, such as genetic and environmental factors, to enhance model precision and applicability. Additionally, incorporating longitudinal data could improve the understanding of addiction progression and relapse patterns. Ethical considerations remain paramount, ensuring the model's application avoids stigmatization and upholds privacy standards. By refining and expanding this approach, machine learning models can become powerful tools for developing personalized prevention and intervention strategies, ultimately contributing to better public health outcomes.

REFERENCES

[1] K. M. Rashedul Alam, K. Ahammed, M. A. T. Rony, and Z. Ferdousi, "A Comparative Machine Learning Study to Predict Drug Addiction in Bangladesh," 2021 IEEE 15th International Conference on Application of Information and Communication Technologies (AICT). IEEE, Oct. 13, 2021. doi: 10.1109/aict52784.2021.9620453.

[2] Shahriar, F. Faisal, S. U. Mahmud, A. Chakrabarti, and M. G. Rabiul Alam, "A Machine Learning Approach to Predict Vulnerability to Drug Addiction," 2019 22nd International Conference on Computer and Information Technology (ICCIT). IEEE, Dec. 2019. doi: 10.1109/iccit48885.2019.9038605.

[3] W. Abada and A. Bouramoul, "Using Machine Learning Techniques to Predict People At-Risk for Drug Addiction: A Bayesian-Based Model," 2022 4th International Conference on Pattern Analysis and Intelligent Systems (PAIS). IEEE, Oct. 12, 2022. doi: 10.1109/pais56586.2022.9946914.

[4] D. M. Haddab, "Data Driven Decision Making in Manufacturing Businesses in China and Asia Pacific," International Journal for Global Academic & Scientific Research, vol. 2, no. 3. International Consortium of Academic Professionals for Scientific Research, pp. 31–42, Oct. 01, 2023. doi: 10.55938/ijgasr.v2i3.57.

[5] K. K. Mak, K. Lee, and C. Park, "Applications of machine learning in addiction studies: A systematic review," Psychiatry Research, vol. 275. Elsevier BV, pp. 53–60, May 2019. doi: 10.1016/j.psychres.2019.03.001.

[6] V. Sharma, "A Study on Data Scaling Methods for Machine Learning," International Journal for Global Academic & Scientific Research, vol. 1, no. 1. International Consortium of Academic Professionals for Scientific Research, Feb. 23, 2022. doi: 10.55938/ijgasr.v1i1.4.

[7] X. Gu, B. Yang, D. Li, D. Xu, and C. Gu, "Research on the Intelligent Evaluation of Addiction Degree and New Method of Rehabilitation of Drug Addicts," 2020 Chinese Automation Congress (CAC). IEEE, Nov. 06, 2020. doi: 10.1109/cac51589.2020.9326655.

[8] Hadjahmadi, M. H. Ziyaaddini, and M. Mehdi Omid, "Using End-to-End Deep Neural Networks for Diagnosing Drug Addiction from Speech Signals," 2020 6th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS). IEEE, Dec. 23, 2020. doi: 10.1109/icspis51611.2020.9349595.

[9] S. Kaur and R. K. Bawa, "Implementation of an expert system for the identification of drug addiction using decision tree ID3 algorithm," 2017 3rd International Conference on Advances in Computing,Communication & Automation (ICACCA) (Fall). IEEE, Sep. 2017. doi: 10.1109/icaccaf.2017.8344677.

[10] Gong, C. Xie, C. Yu, N. Sun, H. Lu, and Y. Xie, "Psychosocial Factors Predict the Level of Substance Craving of People with Drug Addiction: A Machine Learning Approach," International Journal of Environmental Research and Public Health, vol. 18, no. 22. MDPI AG, p. 12175, Nov. 19, 2021. doi: 10.3390/ijerph182212175.

[11] C. Bharat et al., "Development and evaluation of a risk algorithm predicting alcohol dependence after early onset of regular alcohol use," Addiction, vol. 118, no. 5. Wiley, pp. 954–966, Jan. 31, 2023. doi: 10.1111/add.16122.

[12] X. Gu, B. Yang, D. Li, D. Xu, and C. Gu, "Research on the Intelligent Evaluation of Addiction Degree and New Method of Rehabilitation of Drug Addicts," 2020 Chinese Automation Congress (CAC). IEEE, Nov. 06, 2020. doi: 10.1109/cac51589.2020.9326655.

[13] P. Kaushik, S. P. Singh Rathore, P. Kaur, H. Kumar, and N. Tyagi, "Leveraging Multiscale Adaptive Object Detection and Contrastive Feature Learning for Customer Behavior Analysis in Retail Settings," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 6s. Auricle Technologies, Pvt., Ltd., pp. 326–343, Jun. 11, 2023. doi: 10.17762/ijritcc.v11i6s.6938.

[14] B. Chhetri, L. M. Goyal, and M. Mittal, "How machine learning is used to study addiction in digital healthcare: A systematic review," International Journal of Information Management Data Insights, vol. 3, no. 2. Elsevier BV, p. 100175, Nov. 2023. doi: 10.1016/j.jjimei.2023.100175.

[15] P. Agarwal and A. Vij, "Assessing the Challenges and Opportunities of Artificial Intelligence in Indian Education," International Journal for Global Academic & Scientific Research, vol. 3, no. 1. International Consortium of Academic Professionals for Scientific Research, pp. 36–44, Apr. 04, 2024. doi: 10.55938/ijgasr.v3i1.71.

[16] Md. A. Ismail and A. Islam, "Study on the Analysis and Prediction of Drug Addiction Among University Students of Bangladesh Using Machine Learning," Lecture Notes in Networks and Systems. Springer Nature Singapore, pp. 181–196, 2024. doi: 10.1007/978-981-99-8937-9_13.

[17] P. Kaushik and S. P. S. Rathore, "Deep Learning Multi-Agent Model for Phishing Cyber-attack Detection," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 9s. Auricle Technologies, Pvt., Ltd., pp. 680–686, Aug. 31, 2023. doi: 10.17762/ijritcc.v11i9s.7674.

[18] Y.C. Huang, Y.C. Cheng, M.J. Jhou, M. Chen, and C.J. Lu, "Integrated Machine Learning Decision Tree Model for Risk Evaluation in Patients with Non-Valvular Atrial Fibrillation When Taking Different Doses of Dabigatran," International Journal of Environmental Research and Public Health, vol. 20, no. 3. MDPI AG, p. 2359, Jan. 29, 2023. doi: 10.3390/ijerph20032359.

[19] T. V. Lim and K. D. Ersche, "Theory-driven computational models of drug addiction in humans: Fruitful or futile?," Addiction Neuroscience, vol. 5. Elsevier BV, p. 100066, Mar. 2023. doi: 10.1016/j.addicn.2023.100066.

[20] P. Kaushik, R. Rohilla, P. Walia, S. Shankar, M. M. Kaushik and T. S. Gupta, "Confronting Hate Speech in SMART Environments: An Approach that Uses Ensemble Learning and LSTM," 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-6, doi: 10.1109/ICSD60021.2024.10751441.

[21] S. S. Sikarwar, N. Chawla, P. Agarwal, M. F. Afzal, S. P. S. Rathore and N. Valecha, "Improving Lane Management: Leveraging OpenCV and IoT to Empower Smart Environments," 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-5, doi: 10.1109/ICSD60021.2024.10751495.

[22] S. Tanwar, N. Choudhary, V. Chaudhary, A. Dahiya, P. Kaushik and R. Rathore, "Advancing Healthcare: CNN-Based Brain Hemorrhage Detection in Intelligent Environments," 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-6, doi: 10.1109/ICSD60021.2024.10751290.

[23] M. M. Kaushik, M. Kakkar, M. Yadav, P. Kaushik, S. Jha and V. Jaitwal, "Smart Road Segmentation from Aerial Images," 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2024, pp. 1-6, doi: 10.1109/ICSD60021.2024.10751072.