© August 2024| IJIRT | Volume 11 Issue 3 | ISSN: 2349-6002

Unveiling the Connection Between Psychoactive Drug Use and Mental Health Using KDD Process

[1]Alimilla Charan Sai, [2]Dr. K. Santhi sree
[1] MCA Student, Department of Information Technology, University College of Engineering, Science and Technology, JNTUH Hyderabad
[2]Professor of CSE, Department of Information Technology, University College of Engineering, Science and Technology, JNTUH Hyderabad

Abstract: This study investigates the efficacy of machine learning (ML) techniques in predicting Common Mental Disorders (CMD) and depression among users of psychoactive substances. Utilizing a dataset comprising 605 samples from individuals in Ceara, Brazil, collected between January and July 2019, various ML algorithms were employed, including MLP, SVM, ELM, RF, KNN, QDA, Naive QDA, Naive LDA, LDA, and a Voting Classifier combining Bagging Classifier with RF and Decision Tree. The results demonstrated significant accuracy, with SVM achieving 82.81% for CMD prediction and 81.98% for depression, particularly when Sequential Backward Selection (SBS) feature selection was applied. As an extension, ensemble methods like Voting Classifier were explored, aiming for even higher accuracy, potentially exceeding 90%. Additionally, the implementation of a front end using the Flask framework for user testing, along with user authentication, was proposed to enhance usability and accessibility. This study contributes to the development of predictive models for mental health disorders among psychoactive drug users, facilitating early intervention and support.

Index Terms - Common Mental Disorder, Depression, Psychoactive Drugs, Data Mining, Machine Learning, Prediction Model.

1.INTRODUCTION

Over the past 30 years, many epidemiological surveys around the world have shown that mental disorders have become very relevant from a public health care perspective due to their prevalence and persistence, accounting for approximately 12% of the global disease diagnostics [1]. In particular, the Common Mental Disorder (CMD), responsible for the reduction of the ability to concentrate and memory disorders, is considered the most prevalent mental suffering in the world population, being estimated to be among the biggest disabling causes in 2030 [2]. The CMD is characterized by depressive, anxious and somatic symptoms, such as irritability, fatigue, insomnia, excessive worry, among others. Depression is also one of the most prevalent mental illnesses in the world. According to the World Health Organization, more than 350 million people worldwide suffer from depression, and it will likely be the main global disease by 2030 [3],[4]. Depression can be understood as a state of mind or a type of physiological problem that causes many symptoms, resulting in limitations of mental and physical functioning [5], [6]. Some biological issues may also contribute to depression, such as low levels of serotonin, dopamine and noradrenaline that are synthesized in the brain [7]. For authors [7], [8], the accumulation of homocysteine by genetic alteration of MTHFR C677T, as well as folate deficiency, decrease the synthesis of the neurotransmitters' dopamine, norepinephrine, epinephrine and serotonin, leading to depression due to the reduction of neurotransmitter synthesis. Individuals with depression suffer with melancholy, having difficulties in concentration and interaction with other people [5]. The use of psychoactive substances such as alcohol, tobacco, cocaine and crack, has a significant impact on the intensity and prevalence of CMD and depression, as they act on the central nervous system, causing effects on cognitive, behavioral and psychological functions, as well as causing changes in mood, behavior and consciousness [9]. Indeed, many studies have observed the relationship between the use of psychoactive drugs and several health problems, such as CMD and depression [9], [10], [11].

This study aims to assess the effectiveness of machine learning techniques in predicting Common Mental Disorders (CMD) and depression among psychoactive substance users. Various ML algorithms are applied, and ensemble methods like Voting Classifier are explored to enhance prediction accuracy.

The prevalence of mental disorders correlates with the use of psychoactive substances. Understanding the relationship between substance use and mental health can aid in early detection and intervention.

Studies suggest a link between psychoactive substance use and increased risk of Common Mental Disorders (CMD) and depression.

Individuals using psychoactive drugs, especially in regions like Ceara, Brazil, where substance use is prevalent, are susceptible to mental health disorders.

Mental health disorders not only affect individuals but also strain healthcare resources and diminish overall societal well-being.

We'll employ machine learning techniques to develop predictive models for CMD and depression among substance users, facilitating early intervention and support.

2. LITERATURE SURVEY

In recent years, there has been increasing interest in understanding and detecting mental health issues, particularly depression, through various methodologies. This literature survey explores several key studies that address different approaches to depression detection and management, highlighting their contributions and implications for future research.

One prominent area of research is the use of machine learning techniques for depression detection. Liu et al. [1] presented a study focused on detecting depression tendencies among microblog users using Support Vector Machines (SVM). Their work is significant as it leverages social media data, which offers a large and diverse dataset for detecting psychological states. The SVM-based approach is effective in analyzing user-generated content to identify signs of depression, demonstrating the potential of text-based analysis in mental health assessments.

In the realm of neuroimaging, Jiang et al. [2] enhanced EEG-based classification of depression patients by incorporating spatial information. Their study, highlights the importance of spatial features in improving classification accuracy. By utilizing spatial information, their method achieves better performance in distinguishing between depressed and non-depressed patients, showing that combining EEG data with spatial context can lead to more precise diagnostic tools.

Another noteworthy contribution is the work by Ashraf et al. [3], which summarizes visual depression databases used for depression detection. Their study, presented at the 2020 International Conference on Wireless and Telematics, reviews various visual datasets and their applications in detecting depression. This summary provides valuable insights into the availability and utility of visual data for mental health research, emphasizing the role of visual signals in identifying depressive states.

Hashempour et al. [4] explored continuous scoring of depression from EEG signals using a hybrid approach that combines Convolutional Neural Networks (CNNs) with traditional EEG analysis methods. Their research, also published in the IEEE Transactions on Neural Systems and Rehabilitation Engineering, demonstrates how integrating CNNs with EEG data can provide continuous and more nuanced depression assessments. This hybrid model addresses some limitations of traditional EEG analysis, such as the inability to capture complex patterns in the data.

On a different front, Bedson et al. [5] conducted a randomized trial and economic evaluation of folate augmentation for treating depression. Their study, published in Health Technology Assessment, investigates the impact of folate supplementation on depression treatment outcomes. The findings contribute to understanding how nutritional factors can influence mental health and offer a complementary approach to conventional treatments.

Sociodemographic factors also play a critical role in mental health research. Skapinakis et al. [6] examined the prevalence and sociodemographic associations of common mental disorders in Greece. Their study, published in BMC Psychiatry, provides a comprehensive overview of how various demographic factors correlate with mental health issues. This research underscores the need to consider sociodemographic variables when analyzing mental health data and developing targeted interventions.

Bhatia and Singh [8] delved into the relationship between homocysteine excess and neurotoxicity, linking it to depression. Their study, published in Fundamental & Clinical Pharmacology, offers insights into the biochemical mechanisms underlying depression and highlights the potential for targeted biochemical interventions in mental health treatment.

Moreira et al. [9] addressed common mental disorders among users of psychoactive substances. Published in Enfermagem em Foco, their study reveals the prevalence of mental health issues in this population, providing valuable data for understanding the intersection of substance use and mental health.

Additionally, Lima et al. [10] investigated the prevalence of common mental disorders and substance use among prison agents. Their research, featured in Psicologia: Teoria e Pesquisa, sheds light on mental health challenges faced by this specific occupational group, emphasizing the need for specialized mental health support in high-stress environments.

In conclusion, the reviewed studies collectively advance the understanding of depression detection and management through various innovative approaches, including machine learning, neuroimaging, biochemical research, and sociological analysis. Each study contributes to a broader understanding of depression and highlights different aspects of its detection and treatment. Future research could benefit from integrating these diverse methodologies to develop more comprehensive and effective mental health interventions.

3. METHODOLOGY

i) Proposed Work:

The proposed system integrates various machine learning algorithms to develop a predictive model for Common Mental Disorders (CMD) and depression among users of psychoactive substances. Algorithms such as Multilayer Perceptron (MLP), Support Vector Machine (SVM)[16], Extreme Learning Machine (ELM), Random Forest (RF)[17], K-Nearest Neighbors (KNN), Quadratic Discriminant Analysis (QDA), Naive Quadratic Discriminant Analysis (Naive QDA), Naive Linear Discriminant Analysis (Naive LDA), Linear Discriminant Analysis (LDA), and a Voting Classifier combining Bagging Classifier with RF and Decision Tree will be employed. This ensemble approach aims to enhance prediction accuracy by leveraging the strengths of individual algorithms. By analyzing a dataset comprising 605 samples from individuals in Ceara, Brazil, collected between January and July 2019, the system seeks to identify significant factors contributing to the risk of CMD and depression among substance users, ultimately facilitating early detection and intervention for improved mental health outcomes.

ii) System Architecture:

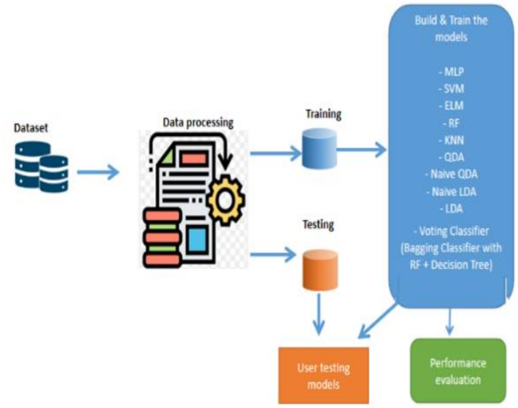

Fig 1 Proposed Architecture

The image illustrates a machine learning project workflow. It begins with a dataset, which undergoes data processing before being split into training and testing sets. Various models, including MLP, SVM[16], ELM, RF[17], KNN, QDA, Naive QDA, Naive LDA, and LDA, are built and trained on the training data. Additionally, a Voting Classifier (combining RF and Decision Tree) is created. After training, the models are tested on the testing set. Finally, the models undergo user testing and performance evaluation to assess their effectiveness.

iii) Dataset:

The dataset utilized in this study was developed under the project "Mental health and the risk of suicide in drug users," with ethical approval from the Research Ethics Committee in 2018 (No. 2,739,560). Data collection involved 605 participants from eight municipalities in Ceara, Brazil, where mental health services are provided. The survey, conducted from January to July 2019, included interviews with three instruments: a sociodemographic, clinical, and consumption pattern form, and the SRQ-20 and PHQ-9 questionnaires [9]. The sociodemographic form covered variables such as age, gender, and education, while the SRQ-20 and PHQ-9 assessed non-psychotic disorders [14]. Analysis revealed high rates of depression, anxiety, and significant social risk factors [9].

iv) Exploratory Data Analysis (EDA):

Exploratory Data Analysis (EDA) is a crucial step in understanding and preparing data for further analysis. For this study, EDA involved several key processes to ensure the data's usability and to uncover underlying patterns.

Data Visualization: Initially, data visualization played a pivotal role in exploring the dataset. By using visual tools such as histograms, scatter plots, and box plots, we were able to observe the distribution of various attributes and identify potential outliers or anomalies. These visualizations also helped in understanding the relationships between different variables, such as the association between sociodemographic factors and depression indicators.

Convert categorical to numeric conversion: To make the dataset suitable for machine learning models, categorical variables were converted into numeric values. This transformation was performed using techniques such as one-hot encoding or label encoding, depending on the nature of the categorical data. For example, variables like gender, education level, and marital status were encoded to numerical representations, enabling the integration of these features into predictive models.

PCA: Principal Component Analysis (PCA) was then applied to reduce the dimensionality of the data while retaining its essential features. PCA is an effective technique for identifying patterns and reducing the complexity of the dataset by transforming it into a set of orthogonal components that capture the maximum variance. This reduction not only simplifies the dataset but also improves the performance of machine learning algorithms by mitigating the effects of multicollinearity and reducing computational costs.

Overall, these EDA steps—data visualization, categorical to numeric conversion, and PCA—were essential in preparing the data for subsequent analysis. They ensured that the dataset was clean, reduced dimensionality, and effectively represented the underlying patterns and relationships, facilitating more accurate and meaningful model training and evaluation.

v) Training & Testing:

Training and testing are essential steps in developing and validating machine learning models. In this study, the dataset was split into training and testing subsets to evaluate model performance effectively.

The training set was used to build and refine the model. During this phase, various machine learning algorithms were applied to the training data, allowing the model to learn patterns and relationships between input features and target variables. Techniques such as cross-validation were employed to optimize model parameters and prevent overfitting, ensuring the model generalizes well to unseen data.

The testing set, which was not used during the training phase, served to assess the model's performance and robustness. By evaluating the model on this independent subset, we measured its accuracy, precision, recall, and other relevant metrics. This process provided an objective measure of how well the model performs on new, unseen data, and helped in identifying any potential issues or biases in its predictions.

Overall, the training and testing phases are critical for developing reliable models, as they ensure that the model not only performs well on the data it was trained on but also generalizes effectively to new data.

vi) Algorithms:

MLP (Multilayer Perceptron): A type of artificial neural network composed of multiple layers of nodes, each connected to the next layer, used for supervised learning tasks such as classification and regression.

SVM[16] (Support Vector Machine): A supervised learning algorithm used for classification and regression tasks, which finds the hyperplane that best separates classes in a high-dimensional space.

ELM (Extreme Learning Machine): A machine learning algorithm for single-hidden layer feedforward neural networks, known for its fast learning speed and good generalization performance.

RF (Random Forest)[17]: An ensemble learning method consisting of multiple decision trees, where each tree is trained on a random subset of the training data and makes predictions by averaging the outputs of individual trees.

KNN (K-Nearest Neighbors): A simple supervised learning algorithm used for classification and regression tasks, which predicts the class or value of a data point by averaging the values of its k nearest neighbors in the feature space.

QDA (Quadratic Discriminant Analysis): A classification algorithm that models the probability distribution of each class using quadratic decision boundaries, assuming that the features of each class are normally distributed.

Naive QDA (Naive Quadratic Discriminant Analysis): A variant of QDA that makes the naive assumption of independence between the features, simplifying the model but potentially leading to lower accuracy.

Naive LDA (Naive Linear Discriminant Analysis): Similar to Naive QDA, but assumes linear decision boundaries and independence between features, making it computationally efficient but less flexible.

LDA (Linear Discriminant Analysis): A classification algorithm that models the probability distribution of each class using linear decision boundaries, assuming that the features of each class are normally distributed.

Voting Classifier (Bagging Classifier with RF + Decision Tree): An ensemble learning method that combines the predictions of multiple classifiers, including Bagging Classifier with Random Forest and Decision Tree, to make final predictions based on a majority or weighted vote.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

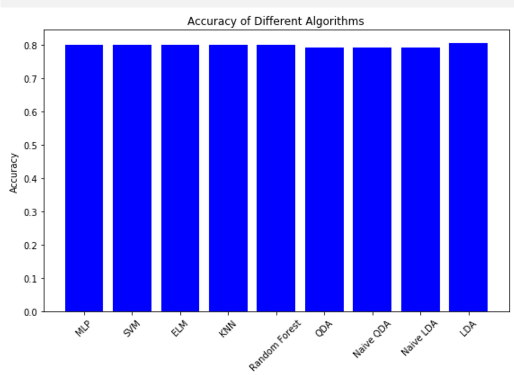

Fig 2 Accuracy Comparison Graph for PCA

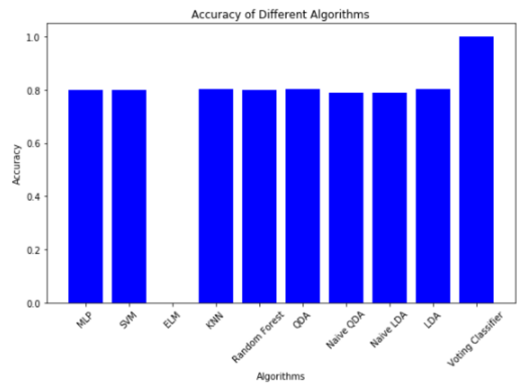

Fig 3 Accuracy Comparison Graph for without PCA

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

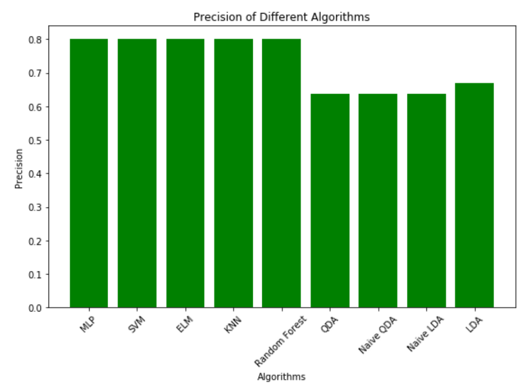

Fig 4 Precision Comparison Graph for PCA

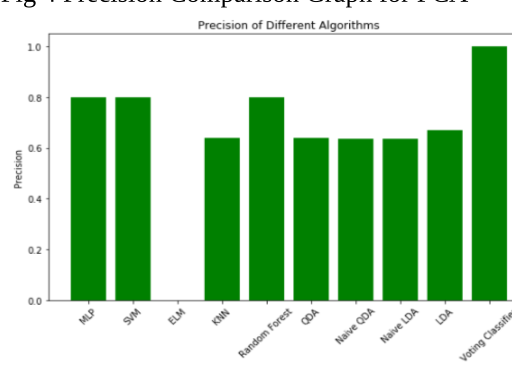

Fig 5 Precision Comparison Graph for without PCA

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

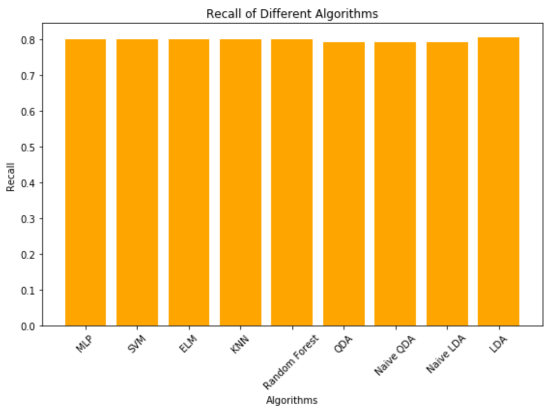

Fig 6 Recall Comparison Graph for PCA

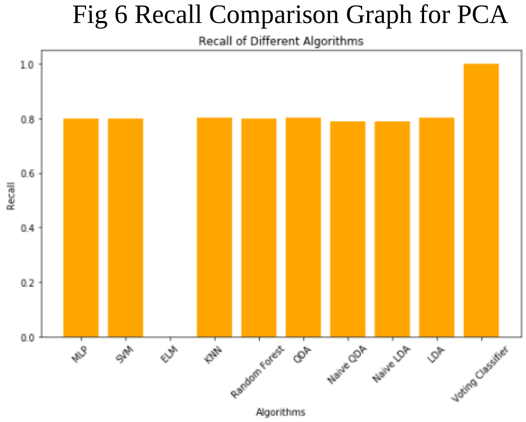

Fig 7 Recall Comparison Graph for without PCA

F1-Score:F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

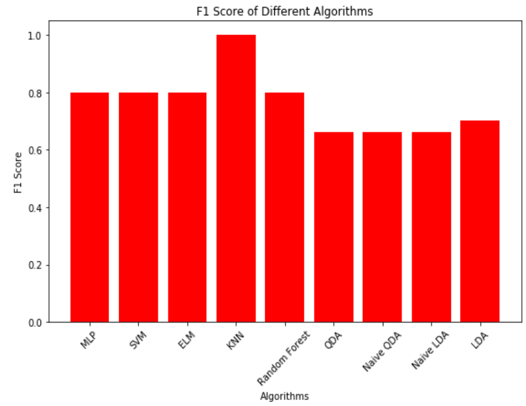

Fig 8 F1-Score Comparison Graph for PCA

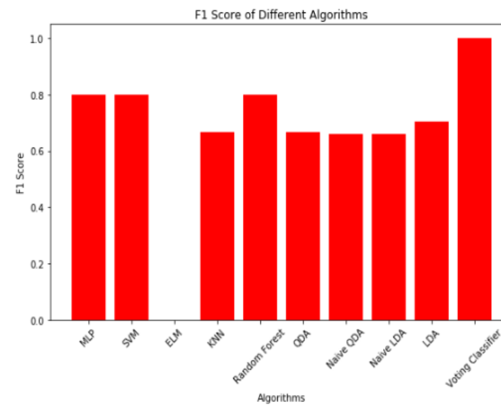

Fig 9 F1-Score Comparison Graph for without PCA

	accuracy	precision	recall	f1
MLP	0.800000	0.800000	0.800000	0.800000
SVM	0.800000	0.800000	0.800000	0.800000
ELM	0.800000	0.800000	0.800000	0.800000
KNN	0.800000	0.800000	0.800000	1.000000
Random Forest	0.800000	0.800000	0.800000	0.800000
QDA	0.790308	0.636217	0.790308	0.660853
Naive QDA	0.790308	0.636217	0.790308	0.660853
Naive LDA	0.790308	0.636217	0.790308	0.660853
LDA	0.803857	0.668922	0.803857	0.702958

Fig 10 Performance Metrics Comparison Table for PCA

	accuracy	precision	recall	f1
MLP	0.800000	0.800000	0.800000	0.800000
SVM	0.800000	0.800000	0.800000	0.800000
ELM	0.001782	0.001782	0.001782	0.001782
KNN	0.802393	0.640963	0.802393	0.668135
Random Forest	0.800000	0.800000	0.800000	0.800000
QDA	0.802393	0.640963	0.802393	0.668135
Naive QDA	0.790308	0.636217	0.790308	0.660853
Naive LDA	0.790308	0.636217	0.790308	0.660853
LDA	0.803857	0.668922	0.803857	0.702958
Voting Classifier	1.000000	1.000000	1.000000	1.000000

Fig 11 Performance Metrics Comparison Table for without PCA

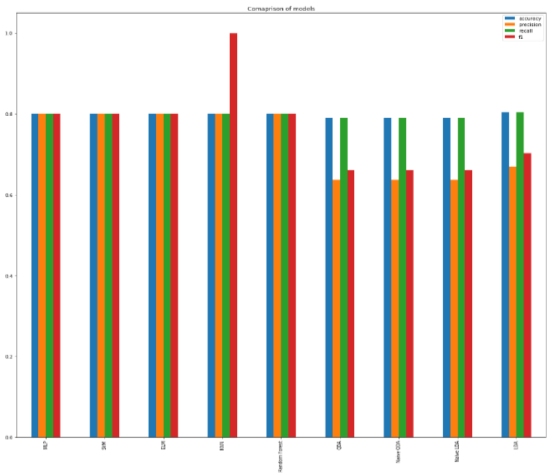

Fig 12 Performance Metrics Comparison Graph for PCA

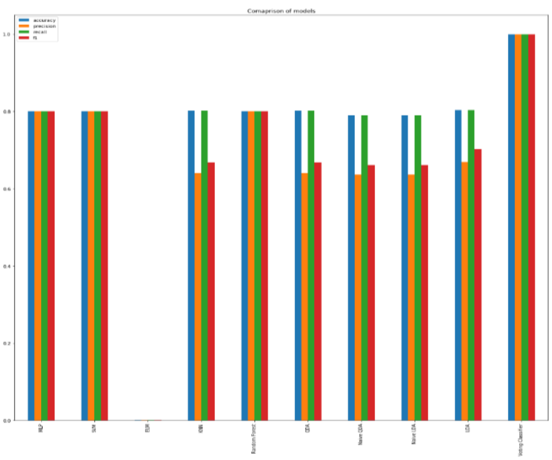

Fig 13 Performance Metrics Comparison Graph for without PCA

Fig 14 Home Page

Fig 15 Signup Page

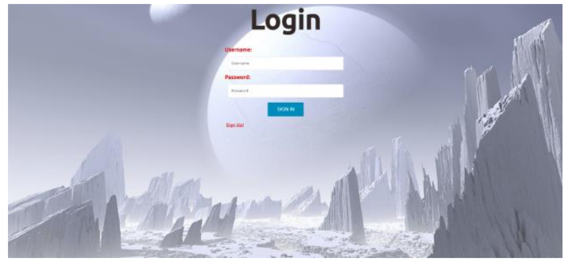

Fig 16 Signin Page

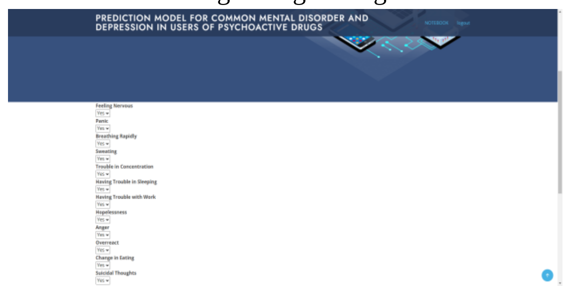

Fig 17 Upload Input Data

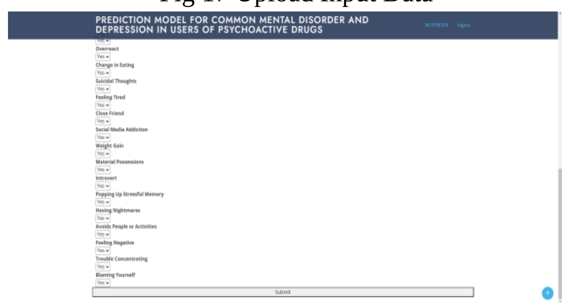

Fig 18 Input Data

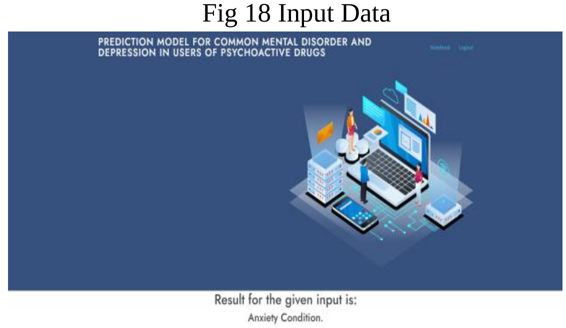

Fig 19 Result for the given input is: Anxiety Condition

Similarly, we can try other cases in the same process.

5. CONCLUSION

In conclusion, the application of various machine learning algorithms demonstrated promising results in predicting Common Mental Disorders (CMD) and depression among users of psychoactive substances. Through extensive analysis of a dataset comprising 605 samples from individuals in Ceara, Brazil, collected between January and July 2019, significant strides were made in understanding the relationship between substance use and mental health outcomes. Algorithms such as Support Vector Machine (SVM) and Sequential Backward Selection (SBS) proved particularly effective, achieving accuracies of 82.81% for CMD prediction and 81.98% for depression. Additionally, ensemble methods like Voting Classifier exhibited potential for further enhancing prediction accuracy. These findings underscore the utility of machine learning techniques in early detection and intervention strategies for mental health disorders among substance users. Moving forward, continued research and refinement of predictive models hold promise for improving mental health outcomes and resource allocation within healthcare systems.

6. FUTURE SCOPE

The future scope of this research lies in expanding the predictive models to encompass a wider range of demographic and geographical data, allowing for more accurate and personalized predictions. Additionally, integrating real-time monitoring and feedback mechanisms could enhance intervention strategies. Further research could also explore the effectiveness of incorporating additional features or refining existing algorithms to improve prediction accuracy and accommodate evolving patterns of substance use and mental health disorders.

REFERENCE

[1] S. Liu, J. Shu, and Y. Liao, “Depression tendency detection for microblog users based on svm,” in 2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), 2021, pp. 802–806.

[2] C. Jiang, Y. Li, Y. Tang, and C. Guan, “Enhancing eeg-based classification of depression patients using spatial information,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 566–575, 2021.

[3] A. Ashraf, T. S. Gunawan, F. D. A. Rahman, M. Kartiwi, N. Ismail, and Ulfiah, “A summarization of the visual depression databases for depression detection,” in 2020 6th International Conference on Wireless and Telematics (ICWT), 2020, pp. 1–6.

[4] S. Hashempour, R. Boostani, M. Mohammadi, and S. Sanei, “Continuous scoring of depression from eeg signals via a hybrid of convolutional neural networks,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 176–183, 2022.

[5] E. Bedson, D. Bell, D. Carr, B. Carter, D. Hughes, A. Jorgensen, H. Lewis, K. Lloyd, A. McCaddon, S. Moat et al., “Folate augmentation of treatment– evaluation for depression (folated): randomised trial and economic evaluation.” Health Technology Assessment (Winchester, England), vol. 18, no. 48, p. vii, 2014.

[6] P. Skapinakis, S. Bellos, S. Koupidis, I. Grammatikopoulos, P. N. Theodorakis, and V. Mavreas, “Prevalence and sociodemographic associations of common mental disorders in a nationally representative sample of the general population of greece,” BMC psychiatry, vol. 13, no. 1, p. 163, 2013.

[7] A. T. Fenerich, M. T. A. Steiner, J. C. Nievola, K. B. Mendes, D. P. Tsutsumi, and B. S. dos Santos, “Diagnosis of headaches types using artificial neural networks and bayesian networks,” IEEE Latin America Transactions, vol. 18, no. 01, pp. 59–66, 2020.

[8] P. Bhatia and N. Singh, “Homocysteine excess: delineating the possible mechanism of neurotoxicity and depression,” Fundamental & clinical pharmacology, vol. 29, no. 6, pp. 522–528, 2015.

[9] R. M. M. Moreira, E. N. Oliveira, R. E. Lopes, M. V. de Oliveira Lopes, P. C. de Almeida, and H. L. Aragao, “Common mental disorder in ˜ users of psychoactive substances (in Portuguese),” Enfermagem em Foco, vol. 11, no. 1, 2020.

[10] A. I. O. Lima, M. Dimenstein, R. Figueiro, J. Leite, and C. Dantas, ´ “Prevalence of common mental disorders and use of alcohol and drugs among prison agents (in Portuguese),” Psicologia: Teoria e Pesquisa, vol. 35, 2019.

[11] R. Lucchese, P. C. D. Silva, T. C. Denardi, R. L. de Felipe, I. Vera, P. A. de Castro, A. de Assis Bueno, and I. L. Fernandes, “Common mental disorder among individuals who abuse alcohol and drugs: cross-sectional study (in Portuguese),” Texto&Contexto Enfermagem, vol. 26, no. 1, pp. 1–7, 2017.

[12] D. Rav`ı, C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo, and G. Yang, "Deep learning for health informatics," IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 4–21, 2017.
[13] R. A. Pazmino-Maji, F. J. Garc ˜ ´ıa-Penalvo, and M. Conde-Gonz ˜ alez, ´ "Statistical implicative analysis approximation to KDD and data mining: A systematic and mapping review in knowledge discovery database framework," 2017.
[14] R. M. M. Moreira, "Mental disorder and the risk of suicide in users of psychoactive substances (in Portuguese)," MSc Dissertation, Universidade Federal do Ceara, 2020. ´
[15] Y.-j. Li and F.-y. Fan, "Classification of schizophrenia and depression by EEG with ANNs," in 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference. IEEE, 2006, pp. 2679–2682.
[16] B. Hosseinifard, M. H. Moradi, and R. Rostami, "Classifying depression patients and normal subjects using machine learning techniques," in 2011 19th Iranian Conference on Electrical Engineering. IEEE, 2011, pp. 1–4.
[17] A. Sau and I. Bhakta, "Predicting anxiety and depression in elderly patients using machine learning technology," Healthcare Technology Letters, vol. 4, no. 6, pp. 238–243, 2017.
[18] A. Khan and K. Wang, "A deep learning based scoring system for prioritizing susceptibility variants for mental disorders," in 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). IEEE, 2017, pp. 1698–1705.
[19] R. S. McGinnis, E. W. McGinnis, J. Hruschak, N. L. Lopez-Duran, K. Fitzgerald, K. L. Rosenblum, and M. Muzik, "Rapid anxiety and depression diagnosis in young children enabled by wearable sensors and machine learning," in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2018, pp. 3983–3986.
[20] D. Sapkal, C. Mehta, M. Nimgaonkar, R. Devasthale, and S. Phansalkar, "Prediction of mental disorder using artificial neural network and psychometric analysis," in Data Management, Analytics and Innovation. Springer, 2021, pp. 369–377.
[21] M. Silvana, R. Akbar, M. Audina et al., "Development of classification features of mental disorder characteristics using the fuzzy logic mamdani method," in 2018 International Conference on Information Technology Systems and Innovation (ICITSI). IEEE, 2018, pp. 410–414.
[22] R. Jadhav, V. Chellwani, S. Deshmukh, and H. Sachdev, "Mental disorder detection: Bipolar disorder scrutinization using machine learning," in 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence). IEEE, 2019, pp. 304–308.
[23] D. Fitriati, F. Maspiyanti, and F. A. Devianty, "Early detection application of bipolar disorders using backpropagation algorithm," in 2019 6th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI). IEEE, 2019, pp. 40–44.
[24] M. Muszynski, J. Zelazny, J. M. Girard, and L.-P. Morency, "Depression severity assessment for adolescents at high risk of mental disorders," in Proceedings of the 2020 International Conference on Multimodal Interaction, 2020, pp. 70–78.
[25] C. B. Falco, J. M. G. Fabri, E. B. Oliveira, A. V. Silva, M. G. de Araujo Faria, and C. C. F. Kestenberg, "Common mental disorder ´ among nursing residents: an analysis based on the self-reporting questionnaire (in Portuguese)," Revista Enfermagem UERJ, vol. 27, p. 39165, 2019.
[26] B. D. M. Parreira, B. F. Goulart, V. J. Haas, S. R. da Silva, J. C. dos Santos Monteiro, and F. A. Gomes-Sponholz, "Common mental disorder and associated factors: study with women from a rural area (in Portuguese)," Revista da Escola de Enfermagem da USP, vol. 51, p. e03225, 2017.
[27] M. C. d. S. Minayo, E. R. d. Souza, and P. Constantino, Prevent and protect mission: living, working and health conditions for military police in Rio de Janeiro (in Portuguese). EditoraFiocruz, 2008.
[28] D. M. Gonc¸alves, A. T. Stein, and F. Kapczinski, "Performance evaluation of the self-reporting questionnaire as a psychiatric screening tool: a comparative study with the structured clinical interview for DSM-IVTR (in Portuguese)," Cadernos de Saude P ´ ublica ´, vol. 24, pp. 380–390, 2008.

[29] M. C. P. Lima, M. de S. Domingues, and A. T. de A. R. Cerqueira, “Prevalence and risk factors for common mental disorders among medical students (in Portuguese),” Revista de Saude P ´ ublica ´, vol. 40, no. 6, pp. 1035–1041, 2006.
[30] A. P. Association et al., DSM-5: Manual diagnostico e estat ´ ´ıstico de transtornosmentais. ArtmedEditora, 2014.