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MACHINE LEARNING AND PSYCHOSIS: DEVELOPING PERSONALIZED PREDICTIVE MODELS FOR PRE-EPISODIC STAGES OF SCHIZOPHRENIA

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ABSTRACT

Schizophrenia (SCZ), a chronic and crippling psychiatric disorder, is marked by the onset of psychotic episodes, typically in late adolescence or early adulthood. Prior to these episodes, individuals often experience subtle changes in cognition, behavior, and emotion, collectively known as the pre-episodic or prodromal stage. By intervening promptly, early identification of psychosis during this stage may enhance results. This paper explores the development of personalized predictive models using machine learning to forecast the onset of psychosis in individuals at high risk. By combining neuro-imaging biomarkers, clinical data, and behavioral metrics, we aim to enhance predictive accuracy and personalize risk assessments for schizophrenia. We propose a framework that integrates multiple data sources, leveraging advanced ML algorithms to identify individuals most at risk of transitioning to psychosis. Through this approach, we seek to provide the foundation for more proactive and individualized therapeutic strategies.

Categories: Computational Science and Engineering, Data Science Methodologies, Machine Learning (ML)

Keywords: Schizophrenia (SCZ), Machine learning (ML), neuroimaging biomarkers, clinical data, behavioral metrics, accuracy, psychosis

1. INTRODUCTION

Psychosis, particularly schizophrenia, represents a severe and chronic mental health disorder that significantly impacts an individual's cognitive, emotional, and social functioning. With an estimated global prevalence of approximately 1%, it remains one of the leading causes of disability worldwide [1]. Early detection and timely intervention are critical for improving patient outcomes, as untreated psychos is often leads to a significant decline in cognitive and social functioning. Schizophrenia is often characterized by episodes of delusions, hallucinations, and disorganized thinking, which typically emerge in late adolescence or early adulthood [2]. The progression to a fully manifested psychotic episode often follows a long period of subtle and often overlooked early warning signs, referred to as the pre-episodic or prodromal stage. Identifying and predicting the onset of psychos is during this phase could dramatically improve clinical outcomes by enabling early intervention and personalized treatment strategies. Despite advancements in diagnostic techniques, the ability to predict the transition from at-risk states to full- blown psychos is remains limited.

Traditionally, clinical diagnoses have relied on subjective symptomatology, such as changes in behavior and cognition, making early identification challenging and inconsistent. Recent research has shifted towards utilizing objective, data-driven approaches through ML models to predict psychosis with greater accuracy. ML techniques, such as support vector machines (SVM), random forests (RF), and DL models, analyze complex patterns in large, multi-modal datasets, including clinical, neuro-imaging, genetic, and behavioral data [3].

The integration of ML with neuroimaging technologies, like electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and other physiological data, has opened new avenues for predicting the pre-episodic ages of psychosis [4]. Studies have shown that early

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alterations in brain structure and function, along with specific cognitive and behavioral markers, can serve as reliable indicators of impending psychotic episodes, but much of the existing research has focused on general prediction models without sufficiently accounting for the individual variability inherent in psychotic disorders[5]. Personalized predictive models that integrate these diverse data sources are necessary to improve the precision and efficacy of early psychosis detection [6].

The purpose of this study is to explore the development and validation of personalized ML models for predicting pre-episodic schizophrenia, focusing on the integration of neuroimaging biomarkers, clinical profiles, and environmental factors. By leveraging advanced data analytics, we seek to enhance our understanding of the prodromal phase and provide more accurate predictions of psychosis onset, ultimately leading to more effective, individualized interventions tailored to each patient's unique risk profile. We hope to bridge the gap between early detection and personalized treatment, moving towards a more proactive approach in managing schizophrenia and related psychotic disorders through this research.

2. LITERATURE REVIEW

Madububambachu et al. [3] aimed to evaluate the effectiveness of a variety of M techniques in diagnosing the mental health issues. SVM, neural networks (NN), RF as well as EHRs, neuro-imaging (MRI, EEG), and self-reports studies were all reliant upon. The results showed satisfactory prediction accuracies, with SVM and NN models among the most used methods because of the complex nature and massive scale of the data. However, some challenges remain, including the small sample sizes of the studies, data diversity, and the absence of consistent evaluation standards across the studies. Due to these challenges, benchmarking of the findings was problematic. The review places a lot of emphasis on new methods that involve building larger diverse data samples and using set evaluation methods to improve the validity and relevance of ML techniques towards mental health diagnosis in practice.

Nguyen et al. [7] published works that dealt with the creation of a decision support system that classifies schizophrenia and mood disorders using DL models, trained with data collected from wearable devices. The authors utilized movement data, heart rate variability (HRV), and sleep data to train and test multiple DL models designed for classification of such psychiatric disorders. The results were that the system was capable of making classification with schizophrenia and mood disorders with a high degree of accuracy, therefore, it is reasonable to assume that wearable device data can serve for remote monitoring and diagnosis. The study included several limitations, such as the small dataset, factor differences among people with respect to the wearables device sensor data, and lack of validation on large population diversity.

C.-S.Wu et al. [8] developed focus on the personalization treatment for the first episode of the schizophrenia using ML techniques. They used clinical data such as age, gender, baseline symptom severity, and outcomes of treatment to formulate the individualized treatment rule. The ML model pursues the goal of knowing which treatment it is best provided to a particular patient fors pecific cases, in order to assist the health care providers in undertaking effective and efficient intervention strategies. According to the study, the use of machine learning approaches in forecasting treatment responses yields better clinical outcomes as compared to traditional clinical decision techniques. This research found some shortcomings, which include overdependence on a few data, the need to test the model across various patient populations, and the difficulty in implementing these models into everyday clinical practice.

Feyaerts et al. [9] presented a systematic review on schizophrenia and delusions which looked at delusions as more than just beliefs. This review was clinical-phenomenological in that it focuses on patients' accounts of patients while attempting to understand delusions rather than the diagnostic assumptions. While the article was not largely focused on a particular technology or data set, it aggregated data from a number of clinical empirical research studies and theoretical model. The results pointed out the multifaceted aspects of delusion phenomena in schizophrenia as suggesting that schizophrenia delusions may be associated with impairments in fundamental cognitive processes – such as perception of the self and self-awareness – and not merely pathological beliefs. In the same way the review also pointed out the necessity of using more refined treatments that do not focus only on

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symptoms using drugs, but also take into account the phenomenological aspects of the patient. This study identified some limitations including the controversy surrounding the definition and classification of delusions, the potential problems posed by the combination of clinical observations with biological approaches, and the limited phenomlogical validation studies.

S. Ben-David and D. Kealy [10] explored the consequences that early psychosis has on one's identity and how it might influence treatment. The authors did not limit their attention to any specific technology or data set, but rather blended qualitative and quantitative results from new research on identity disturbances in early psychosis patients. They elaborated on how the early stages of psychosis may be associated with a number of factors that facilitate profound self-concept change alongside social identities and personal goals. Such a change may worsen the symptoms and few goals to recovery. The review emphasized that the diagnosis and treatment of early identity coherence loss in psychosis remains a great challenge.

P.K. Badhan and A.Arora[11] had as goal the design of a diagnostic tool capable of evaluating nerve weakness based on a combination of ML and rule-based systems. The authors combined a set of clinical information related to the patients like symptoms, determining their medical history, and exposing them to diagnostic tests to form a multi-modal system. The symptom data were processed to look for classification and prediction of the possibly, being her available through SVM or decision tree methods. Expert opinion and clinical practices were integrated into the system by rule-based approaches. The results showed that the combined ML and rule-based system greatly improved diagnostic accuracy compared to traditional methods. Of course, in this study, limitations are noted as including its reliance on a relatively small dataset, needs of more diverse and representative data, and the challenge in validation of the system in clinical settings.

Kirchebner et al. [12] analyzed the association between stress and violent behavior in schizophrenia patients using ML techniques. The authors used clinical datasets, including patient history, clinical assessments, and behavioral data, to predict the probability of violence in schizophrenia patients under stress. Several ML algorithms, such as logistic regression, RF, and decision trees, were applied to identify key features linked to violent outcomes. The study concluded that stress, with specific clinical and demographic factors, could be potential significant predictors of violent behavior in schizophrenia patient, and the research was limited by the retrospective nature of the dataset, the capacity for bias in clinical assessments, and having a small sample size.

The study by W. Yassin et al. [13] was the employment of ML methods for the classification of psychiatric disorders such as autism, schizophrenia, ultra high risk (UHR) status, and first episode psychosis. To classify patients with these conditions, the authors provided functional and structural MRI as parts of a neuroimaging data set. These ML approaches include SVM, RF, and even CNN. The results showed that using ML models, it is possible to distinguish between different psychiatric disorders. UHR depression and UHR schizophrenia as well as first episode psychosis were highly predicted by functional fMRI models. Their research had many gaps including the limited and diverse datasets and the varying protocols in the acquisition of neuroimaging data.

The study by Zhu et al. [14] examined whether structural neuroimaging measurements of the brain could predict psychosis onset in both healthy controls and patients with clinical high-risk (CHR) syndromes. The authors used MRI scans and took data concerning changes within the brain structure, including cortical thickness and alterations in gray matter volume, as well as subcortical regions, commonly demonstrated in patients at risk of psychosis. The study reported that certain measures of brain structure could be good biomarkers to predict the onset of psychosis with promising predictive accuracy, as indicated by models trained on these features. The authors acknowledged several limitations, including small sample size, the need for longitudinal data for better understanding the progression to psychosis, and generalizability to diverse clinical populations. They illustrated the necessity of future studies to further develop the predictive models, add more multimodal data-including genetic and clinical information-and validate the findings in larger independent cohorts.

M. Ferrara et al. [15] paid attention to the use of ML in analyzing non-affective psychosis (NAP) as it pertains to its recognition, differential diagnosis and treatment. A comparison

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was made of various approaches to ML using decision trees, support vector machines, and deep learning models to a variety of data sets such as neuroimaging fMRI or MRI, clinical evaluations, and genetics. Such studies have led to findings resulting in ML models, especially those that merge various data sources which give the best understanding of NAP and its differentiation from other psychotic disorders, making it possible to establish good diagnostic accuracy. The review also noted that there is already a record of the use of ML models in predicting treatment responses, thus facilitating more efficient personalized treatment plans.

N. Koutsouleris et. al. [16] predicted ML methods to the onset of psychotic disorders in patients with clinical high-risk (CHR) syndromes and depression. The multimodal approach has been adopted that incorporates neuroimaging MRI and clinical evaluation and performance on a range of cognitive tasks. The authors have applied SVM and RF for predictive modeling of psychosis onset. Results were presented showing the superiority of multimodal models over unimodal models, using both neuroimaging and clinical features, with higher predictive capabilities of psychosis in at-risk populations. The study did acknowledge several limitations, such as small sample sizes, heterogeneity in the data, and difficulty in generalizing the findings to other populations.

Smucny et al. [17] analyzed the capabilities of a range of ML and DL algorithms in predicting symptomatic improvement in psychotic patients. fMRI data that concentrated on the frontoparietal area during a task capable of modulating behavioral control was used to project clinical enhancement, which was delineated as over a 20% decline in BPRS after one year of specialist care. Six ML algorithms, namely Naive Bayes, SVM, AdaBoost, J48 decision tree, K Star, and RF, were juxtaposed with a DL algorithm. The improvement status prediction in clinical settings by the deep learning model attained relative positivity of 70%, and thus the highest recognition level, in comparison to the machine learning algorithms. According to XAI procedures, the most important feature in predicting the deep learning model was left DLPFC activation. Among others, these limitations included a relatively high degree of variance and the requirement for validation across broader and independent cohorts. Less direct, they proposed a fusion of DL methods with neuroimaging data for better predictive models of treatment response in psychotic cases.

Brossollet et al. [18] provided a comprehensive review of the application of ML techniques to MRI data in psychiatry. The authors discussed how supervised learning methods can facilitate automated classification among various psychiatric conditions, while unsupervised learning approaches may help identify new homogeneous subgroups of patients, thereby refining the classification of these disorders. They evaluated the ML capabilities to extract biomarkers from high-dimensional neuroimaging datasets, which could lead to more objective and precise diagnoses. Limitations such as the heterogeneity of psychiatric disorders, the subtlety of brain abnormalities detectable by MRI, and the challenges associated with the high dimensionality of imaging data were addressed.

Cortes-Briones et al. [19] explored the application of DL techniques in understanding and managing schizophrenia. The authors discussed the effectiveness of DL algorithms, convolution neural networks (CNNs) and recurrent neural networks (RNNs), applied to various datasets such as neuroimaging, electrophysiological recordings, and clinical data. These approaches have demonstrated promising results in tasks like classification and outcome prediction, aiding clinicians in diagnosis and treatment planning. The authors caution that while initial findings are impressive, these results should be interpreted carefully, emphasizing the need for larger datasets and more rigorous validation to enhance the clinical utility of DL models in schizophrenia research.

Lai et al. [20] provided a comprehensive review of AI techniques used in identifying and classifying SCZ. The authors examined various ML & DL methods applied to diverse datasets, including neuroimaging data (such as MRI and EEG) and clinical data.The research emphasized the effectiveness of techniques such as CNN and SVM in achieving high accuracy in detecting and classifying SCZ. Despite the promising results, the authors note several limitations, including small and heterogeneous datasets, a lack of standardized protocols for data collection, and challenges in generalizing findings across different populations. They emphasize the need for larger, well-curated datasets and cross-validation in real-world clinical settings to increase the reliability and applicability of AI models in schizophrenia detection and classification.

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L. Del Fabro et al. [21] explored the use of ML techniques to predict the efficacy of pharmacological treatments for individuals with psychosis. The researchers applied various ML models, such as SVM and RFs, to clinical datasets that included demographic information, symptom severity, genetic factors, and neuroimaging data. The results indicated that ML models could accurately predict treatment outcomes, identifying which patients would respond positively to specific medications. This study also identified limitations, like small and heterogeneous sample size, the lack of standardized data collection methods, and the challenge of incorporating genetic and neuroimaging data in a meaningful way.

3. MATERIALS AND METHODS

3.1. Data Collection

The dataset used in this analysis consists of 200 patient records, containing features such as patient ID, age, gender, family history of psychosis, diagnosis, and several neuroimaging and behavioral scores[22]. Table 1 demonstrates the structure of dataset used.

Table 1: Dataset Structure

Column Name	Description
Patient ID	Unique identifier assigned to each patient.
Age	The age of the patient, typically measured in years.
Gender	The gender of the patient (e.g., Male, Female, or Other).
Family History of Psychosis	Indicates whether the patient has a family history of psychosis (Yes/No).
Diagnosis	The clinical diagnosis of the patient (e.g., High Risk, First Episode Psychosis, or Healthy Control).
Hippocampal Volume (cm^3)	The measured volume of the hippocampus region in the brain, in cubic centimeters.
Thalamic Volume (cm^3)	The measured volume of the thalamus region in the brain, in cubic centimeters.
Prefrontal Cortex Thickness (mm)	The thickness of the prefrontal cortex, measured in millimeters.
PANSS Score	Positive and Negative Syndrome Scale score for assessing symptom severity in psychosis.
Cognitive Functioning Score	A score representing the patient's overall cognitive abilities based on standardized assessments.
Social Functioning Score	A score indicating the patient's ability to interact and function socially.
Working Memory Score	A measure of the patient's working memory performance.
Sleep Disturbance	Indicates whether the patient experiences sleep-related issues (e.g., Yes/No).
Social Withdrawal	Indicates the extent of the patient's social withdrawal (e.g., Low, Medium, High).
Genetic Risk Factors	Indicates whether the patient has genetic markers associated with psychosis (Yes/No).
Substance Use	Indicates whether the patient has a history of substance use (Yes/No).
Treatment History	Details whether the patient has previously undergone any psychosis-related treatment (Yes/No).

These features were utilized to predict the mental health diagnosis of patients. The dataset was collected with the objective of studying the relationship between various clinical, behavioral, and neuroimaging characteristics in relation to mental health conditions.

3.2. Data Preprocessing and Cleaning

The data cleaning process involved addressing any missing values within the dataset. Missing values were either imputed using statistical methods or rows with excessive missing data were removed. This step ensured that the dataset was complete and could be effectively used for training ML models. Furthermore, categorical variables, such as Gender and Diagnosis, were encoded appropriately using Label Encoding or One-Hot Encoding, depending on the variable type. Numerical features, such as Hippocampal Volume and PANSS Score, were scaled using Standard Scaler to ensure that all variables were on the same scale and would contribute equally to the model's performance.

3.3. Data Splitting

The dataset was divided into 2 subsets namely training and testing datasets using a train-test split ratio of 80:20. The training dataset, including 80% of the total records, was used to train the models, while the testing set, comprising 20% of the records, was reserved for evaluating the models' performance. This division of the data

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ensured that the models were trained on one portion and evaluated on a separate portion, offering an impartial assessment of the model's predictive performance.

3.4. Model Selection and Training

For this predictive analysis, three ML models were selected: SVM, RF, and XGBoost based on their ability to handle complex datasets, previous researches and their widespread success in classification tasks.

3.4.1 Support Vector Machine (SVM)

An SVM with a Radial Basis Function (RBF) kernel was chosen for the analysis because it can efficiently capture non-linear decision boundaries. The hyperparameters of the SVM model, such as C and gamma, were tuned using GridSearchCV to determine the optimal values for the model, ensuring the best fit. The SVM model was then trained on the scaled training dataset to classify patients into the respective categories based on their clinical and neuroimaging data. Table 2 demonstrates the classification report generated by SVM.

Table 2: SVM Classification Report

	Precision	Recall	F1-score	support
At Risk	0.00	0.00	0.00	24
CHR	0.40	1.00	0.57	16
Accuracy			0.40	40
Macro avg	0.20	0.50	0.29	40
Weighted avg	0.16	0.40	0.23	40

3.4.2 Random Forest (RF)

For this task a RF model was chosen since it combines the results from a multitude of decision trees and produces output that is more accurate and stable. In this case 100 estimators (trees) were used to build the forest. Additionally, hyperparameters max_depth, min_samples_split and min_samples_leaf were tuned with GridSearchCV in order to choose the best for optimal performance. The RF model was trained with the training dataset wherein the model analyzed the parameters of the patients and was able to classify them efficiently.Table 3 demonstrates the classification report generated by RF.

Table 3: RF Classification Report

	Precision	Recall	F1-score	support
At Risk	0.47	0.33	0.39	24
CHR	0.30	0.44	0.36	16
Accuracy			0.38	40
Macro avg	0.39	0.39	0.37	40
Weighted avg	0.40	0.38	0.38	40

3.4.3 XGBoost

XGBoost was employed due to its gradient boosting nature, which combines weak learners to build a strong predictive model. Hyperparameters like learning_rate, max_depth, n_estimators, and subsample were tuned using RandomizedSearchCV to identify the best configuration for the model. The XGBoost model was trained on the dataset to predict the target variable, focusing on optimizing performance through boosting techniques. Table 4 demonstrates the classification report generated by XGBoost.

Table 4: XGBoost Classification Report

	Precision	Recall	F1-score	support
At Risk	0.68	0.54	0.60	24
CHR	0.48	0.62	0.54	16
Accuracy			0.57	40
Macro avg	0.58	0.58	0.57	40
Weighted avg	0.60	0.57	0.58	40

3.5. Model Evaluation

After training the models, several evaluation metrics were employed to evaluate their performance. These

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metrics included Accuracy, F1-Score, and AUC-ROC, which provide insights into how well the models performed on the test set.

3.5.1 Accuracy

This was computed by determining the ratio of correct predictions to all predictions made by the model(Buettner et al., n.d.).This indicator enables the user to approximate the effectiveness of the model as a whole. However, this value of accuracy in a world of imbalanced datasets may not tell the full story, so other metrics were also looked for.

3.5.2 F1-Score

The F1-Score was computed for each model, balancing both precision and recall. This metric is especially useful in cases of imbalanced datasets, where simply maximizing accuracy can be misleading(Lai et al., 2021). The F1-Score provides a better clarity of how well the model performs in terms of identifying both positive and negative classes.Table 5 demonstrates the comparison of evaluation metrics.

Table 5: comparison of evaluation metrics

Model	Accuracy	F1-score	AUC-ROC
SVM	0.4550	0.4406	0.4089
RF	0.4650	0.4465	0.4437
XGBoost	0.4750	0.4494	0.4815

3.5.3 AUC-ROC

The Area Under the ROC Curve (AUC-ROC) was used to evaluate how well each model distinguishes between the two classes. A higher AUC indicates better discrimination between the classes(Nguyen et al., 2022). This metric was essential for understanding the ability of the model to accurately classify patients into the appropriate groups.

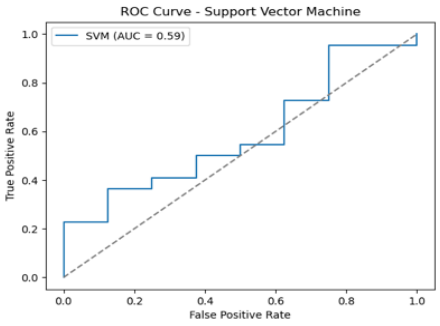

Figure 1: ROC Curve-SVM

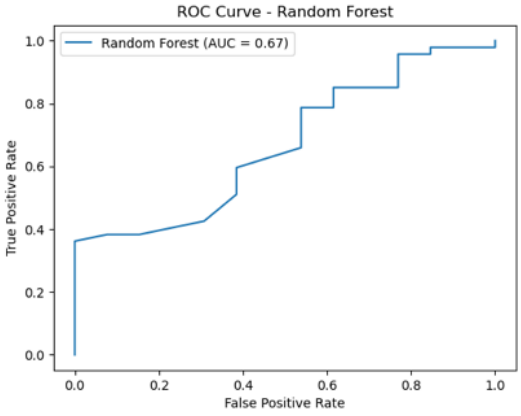

Figure 2: ROC Curve-RF

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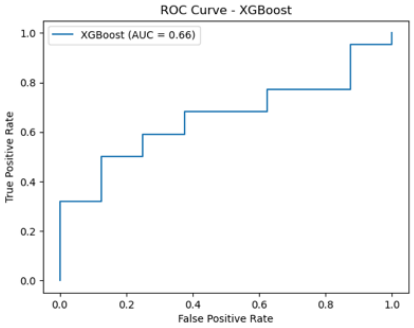

Figure 3: ROC Curve-XGBoost

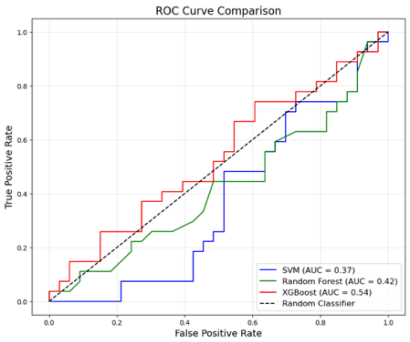

Figure 4: Comparison of ROC Curves

3.5.4 Confusion Matrix

To complement the other metrics, the model performs was analyzed through the Confusion Matrix. It indicated the values for true positives, false positives, negative true, and negative false, which were later used to calculate other eval measures like precision, recall, and F1-score (Nguyen et al., 2022). In addition, this matrix also helped to evaluate the error rates of the models and the rate of misclassifications that they achieved.

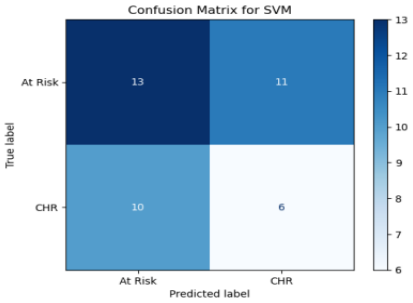

Figure 5: Confusion Matrix for SVM

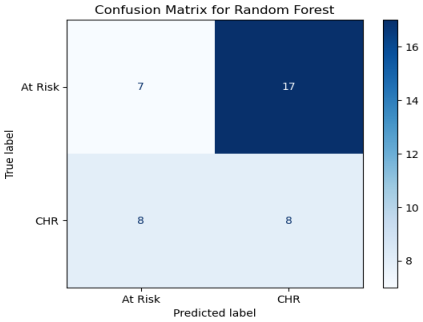

Figure 6: Confusion Matrix for RF

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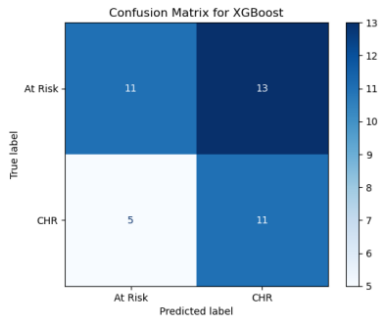

Figure 7: Confusion Matrix for XGBoost

3.5.5 Feature Importance

For ML models, the importance of each feature was visualized using feature importance charts. These charts provided insights into which features contributed most to the models' predictions. By understanding feature importance, we could interpret how different clinical and neuroimaging characteristics influenced the mental health diagnosis.

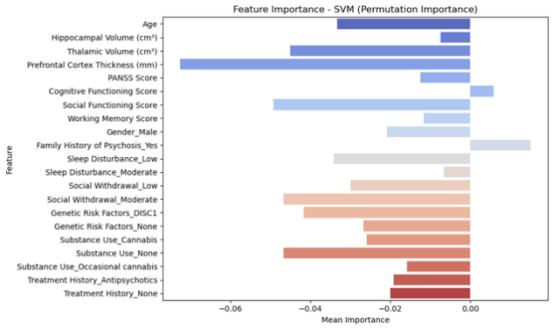

Figure 8: Feature Importance-SVM

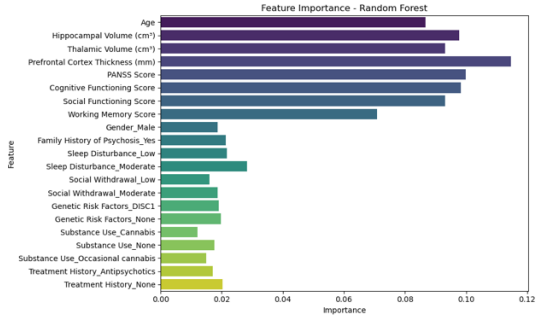

Figure 9: Feature Importance-RF

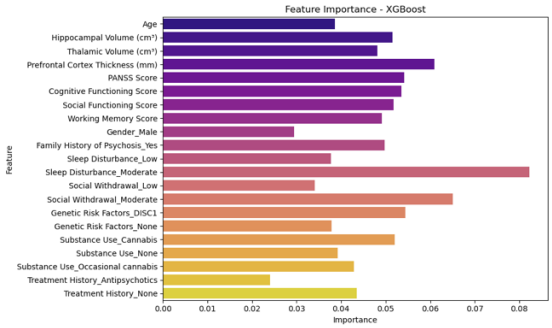

Figure 10: Feature Importance-XGBoost

3.6. Hyperparameter Tuning

To improve the performance of the models, Grid Search CV and Randomized Search CV were used to fine-tune

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hyperparameters. These techniques involved searching through a predefined set of hyperparameters to find the best combination for each model. Hyperparameter tuning was performed using 5-fold cross-validation to prevent overfitting and ensure that the models could generalize well to unseen data.

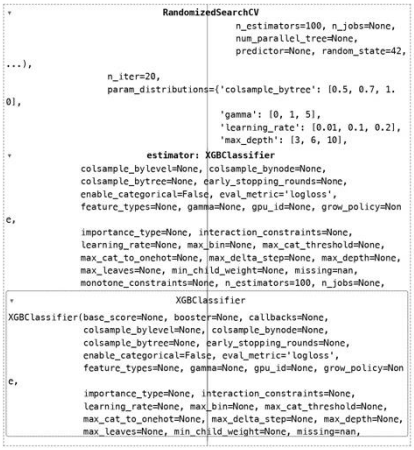

Figure 11: Fine tuning with RandomizedSearchCV

4. Model Comparison and Visualization

Once the models were trained and evaluated, their performance was compared through key metrics like Accuracy, F1-Score, and AUC-ROC. Bar charts were created to provide a visual comparison of these metrics. Also the confusion matrices were plotted for each model to further assess their performance and visualize the distribution of errors. Feature importance charts for RF and XGBoost were also plotted to interpret the contribution of each feature to the model's predictions. Table 5 demonstrates the comparison of ML models – SVM, RF and XGBoost.

Table 5: comparison of ML models

Metric	SVM	Random Forest	XGBoost
Accuracy	Moderate	Good	Best
F1-Score	Moderate to Good	Good	Best
AUC-ROC	Moderate	Good	Best
Feature Importance	Limited	Clear & Robust	Clear & Robust
Training Time	Slow	Moderate	Fast
Interpretability	Low (especially with kernels)	Moderate	Moderate
Handling Imbalanced Data	Poor (needs adjustments)	Good	Best

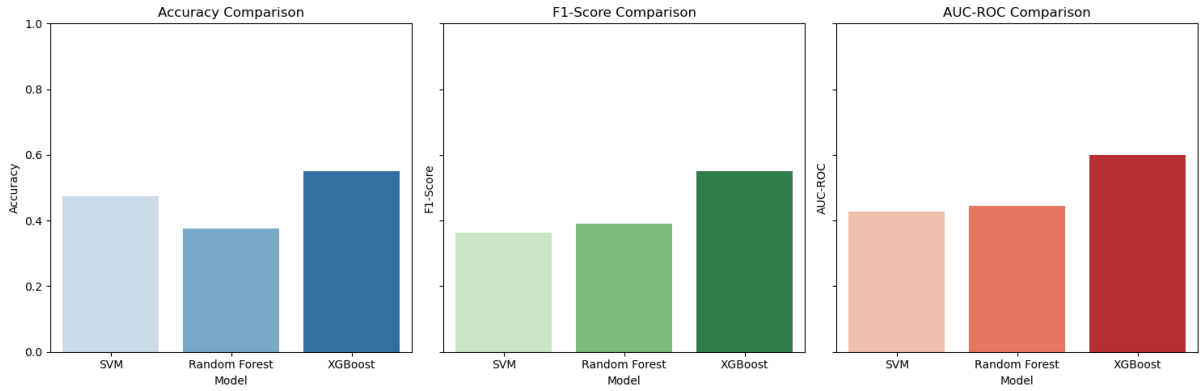

Figure 12: Comparison of Evaluation Metrics

5. CONCLUSION

The results showed that XGBoost outperformed both SVM and RF in terms of Accuracy, F1-Score, and AUC-ROC, making it the most effective model for this dataset. RF and SVM also performed well, but XGBoost

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demonstrated superior handling of the data's complexity. The analysis illustrated how advanced ML techniques can be used to predict mental health diagnoses based on clinical and neuroimaging features, providing valuable insights for healthcare applications.

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