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Hybrid Intelligent EEG-based Framework Integrating Deep Learning and Ensemble Methods for Accurate Early OCD Diagnosis

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***Abstract*— obsessive-compulsive disorder (OCD) is a persistent mental illness that is associated with intrusive thoughts and repetitive actions that considerably affect the normal functioning of the body. One of the greatest issues in the field is early diagnosis as the symptoms are similar and the conventional methods in the diagnosis involve the use of neuroimaging and EEG data which has limitations. The present research offers a composite machine learning and deep learning model of early OCD detection, referring to applying EEG signal processing methods to the combination of the advanced feature extraction and classification algorithms. The model uses the convolutional neural networks coupled with ensemble learning to enhance diagnostic accuracy and solidity. Large-scale EEG experimental assessment shows that performance is better with accuracy of 99.87% with steady cross-validation performance. It is suggested that the proposed approach will maximize the capability of early diagnosis, decrease the misclassification rates, and offer clinicians with a efficient decision-support system with high reliability. The study will help to enhance mental health assessment and promote the significance of diagnostic solutions based on AI.**

***Keywords*— obsessive-compulsive disorder (OCD), Electroencephalography (EEG), Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Ensemble Learning, Feature Extraction, Early Diagnosis, Mental Health Assessment, AI-Based Decision Support System.**

I. INTRODUCTION

Obsessive-compulsive disorder (OCD) is a serious and chronic mental disorder that afflicts millions of people across the globe and seriously impairs their everyday life and daily routine. Mostly those people who experience it are defined by two significant constituents: obsessions which constitute a constant and intrusive thoughts and compulsions which constitute repetitive actions that people engage in order to alleviate anxiety generated by thoughts. OCD patients usually have distress and functional impairment and therefore it is necessary to diagnose and treat them at an early stage in life. Nevertheless, OCD is an underexplored condition although it is quite widespread especially in the early years of the disease since the symptoms are complex and differ in distinct patients. Conventional clinical examination is based on the subjective method of evaluation that may result in late or incorrect diagnosis [1].

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The past years have also seen development of neuroimaging and electroencephalography (EEG) which led to new prospects of understanding the neurological basis of OCD. EEG signals; those that record electric currents within the brain, provide a cost effective and non-invasive means of identifying the abnormalities in neural activity in psychiatric disorders. Nevertheless, the inherent complexity in the interpretation of the EEG data is because of noise, variability and high dimensionality. On the same note, neuroimaging (functional magnetic resonance imaging (fMRI)) can reveal specific details of the brain activity, however, intricate analysis methods are needed to give meaningful biomarkers [2]. All these problems indicate a necessity of automated and smart systems that would be able to process massive biomedical data effectively.

Machine learning (ML) and deep learning (DL), also known as artificial intelligence (AI) have become a strong tool in healthcare diagnosis. ML algorithms can learn patterns given data and make predictions, whereas DL models, like the convolutional neural networks (CNNs) can automatically extract hierarchical features of the raw input signals. The technology has demonstrated potential outcomes in some of the medical fields such as disease classification, anomaly detection, and predictive modeling. Considering OCD, AI-based models may be used to interpret EEG and neuroimaging data and identify less obvious patterns, which may not be identified with traditional techniques [3].

In spite of these developments, the current studies about OCD detection with the help of AI have a number of limitations. Most of the research uses small datasets in research thus limiting the generalization properties of the models. Besides, the majority of approaches rely on either machine or deep learning separately without merits of both. In addition, lack of interpretability, overfitting and inconsistency in the validation process lead to lower reliability of the results. These constraints suggest a high gap in research to develop powerful, precise, and generalizable models to diagnose early OCD [4].

To solve these problems, this paper will give a hybrid architecture that will combine both machine learning and deep learning algorithms to achieve better output in detection of OCD. The suggested model uses the EEG signals as the original sources of information and employs the modern preprocessing methods to eliminate noise and artifact. The deep learning models are used to extract features, and classifications are boosted with the methods of ensemble learning. This combination has the capability of capturing both low level and high level features resulting in better performance and generalization.

The use of a vast dataset together with strict evaluation methods such as cross-validation to test the reliability of the models is also another important contribution of this study. The framework has been developed to attain high accuracy and at the same time be computationally efficient thus suitable in the actual clinical field. Also, the paper focuses more on the importance of early diagnosis, which is essential to successful treatment and improved patient outcomes. Due to the early detection of OCD, the extent of symptoms is minimized, and the healthcare provider will be able to carry out timely measures to increase the overall level of life quality [5].

The application of AI in the mental health diagnosis raises some concerns about the ethical and practical application as well. Most of the issues, like data privacy, model transparency, and clinical acceptance, would have to be solved to achieve successful implementation. Nevertheless, well-validated AI-powered systems can potentially relegate psychiatric diagnostics to a technologically advanced stage. The suggested framework will facilitate this emerging area by offering an effective and dependable way of detecting OCD.

To conclude, OCD is a multifaceted mental illness, which needs a sophisticated diagnostics strategy to be detected at an early stage. Subjectivity and data complexity of the traditional methods have restrictions, whereas the AI can provide an alternative through the automated and data-driven analysis. The presented research proposes a hybrid ML-DL model that would increase the accuracy of diagnostic decisions and provide answers to the current knowledge gap. The results help to reveal the possibilities of combining the EEG analysis and cutting-edge computational methods, which could enhance the diagnostics of mental disorders and clinical judgments

II. Literature Survey

Obsessive-Compulsive Disorder (OCD) is a chronic psychiatric disorder involving persistent intrusive thoughts, behavioral or mental acts that interferes with a person's ability to live a normal life. Because of the complexity of symptoms and their overlap with other mental health diseases, early and correct diagnosis of OCD is still difficult. Automated detection and assessment of OCD has been enhanced with recent progress in artificial intelligence, machine learning, deep learning, neuroimaging and wearables. Different computational methods have been investigated with clinical data, brain signals, brain imaging techniques, and behaviour patterns to increase the accuracy of diagnosis and help early detection, and thus, intervention. Combined with healthcare

systems, intelligent algorithms have shown potential in improving the diagnosis, prediction of severity, monitoring treatment, and raising awareness about OCD.
Research on profound transfer learning method for anxiety disorder prediction with OCD datasets has been performed. A TabNet-based framework proved improved classification performance by using feature selection, data imputation, and transfer-learning mechanisms, allowing for reliable predictions with a minimal issue of overfitting [6]. The AI applications across OCD studies have also been extensively studied, stressing the relevance of electroencephalography (EEG), neuroimaging, and clinical and demographic data for diagnosis and prediction of treatment responses. The review highlighted the increasing significance of machine learning that can be supplemented in clinical decision-making [7].
The use of virtual reality (VR) technologies as innovative tools for the assessment and detection of OCD has been developed. By using immersive virtual environments, clinicians can better see into the patient responsive and record under suitable conditions and enhance the diagnostic precision. These strategies help to simulate realistic scenarios of triggering and assess measurable behavioral indicators which validates traditional assessment strategies [8]. Likewise, machine learning and artificial intelligence methods have been used to make data-driven predictions of OCD by using approaches with support vector machines or a convolutional neural network. These methods have shown feasibility for automation of screening systems that could provide mental health professionals with support to better detect potential OCD cases [9].
The application of serious games has also become a topic of interest in the field of awareness of mental health and visualization of OCD behaviours in interactive environments. Not only do these systems help to better engage the user, they also help to inform a person about the symptoms and psychological effects of OCD. Their usability and reliability have been evaluated through experiments with positive result towards serving as complimentary tools in mental health [10]. In another study they used the models to the latent components of the event related potentials derived from EEG recordings. Utilizing advanced feature extraction and classification techniques, the accurate diagnosis of OCD could be realized, showing the important role of neural signal analysis in objective mental health assessment [11].
Ensemble learning and classification have proven to be effective in comparative studies of machine learning algorithms to predict OCD severity. The Random Forest, Decision Tree, Logistic Regression, and Extreme Gradient Boosting (XGBoost) techniques have been used to classify the severity level of OCD, with the former methods showing better predictive power in general [12]. In addition to this, the use of functional near-infrared spectroscopy (fNIRS) and Gramian Angular Field transformations has further helped diagnose OCD by measuring the hemodynamic responses and using deep learning models for classification. This method proved to be useful in the detection of mental disorders using features extracted from neuroimages [13].
Enhanced prediction of variables such as severity of OCD and comorbid depression has been achieved through the use of multimodal machine learning frameworks with clinical interviews, behavioral data and deep brain stimulation measurements. These systems capitalize on more than one data source to increase the robustness of the diagnosis, and to aid in individualized treatment planning [14]. EEG connectivity analysis has also been studied with various EEG connectivity measures and classifiers (SVM). The results showed that connectivity-based biomarkers have the ability to differentiate between OCD patients and healthy controls and focus on the importance of brain network analysis in psychiatric diagnosis [15].
Several hybrid AIs have been suggested for early-warning of various psychological disorders, among them OCD. These systems are better able to classify certain information and help identify mental health disorders at an early stage by combining both supervised learning and unsupervised learning strategies [16]. Spatial similarity-aware learning combined with Graph Convolutional Networks (GNNs) have also proven valuable in addressing relationships and patterns within neuroimaging data and improving the diagnosis of OCD. These architectures are capable of effectively taking into account structural and functional patterns in the brain of OCD patients [17].
Apart from the diagnostic dimension, research has been used to analyze compulsive behavioral tendencies by conducting consumer behavior analysis, focusing on consumer psychology mechanisms for compulsive behaviors and decision making [18]. There have also been virtual reality-based assessment systems using physiological measures to assess the presence of the symptoms of OCD in the virtual world to provide an objective and interactive diagnostic support [19]. In addition, deep learning approaches based on wearable sensors have been developed to detect actions of approaching the face, often linked to OCD. These have been based on accelerometer and sensor data to look for repeated actions and offer immediate opportunities for intervention using wearable devices, which are showing promise in the management of OCD, amongst other applications [20].

III. METHODOLOGY

The designed methodology implies a hybrid approach that combines both machine learning and deep learning algorithms to detect obsessive-compulsive disorder (OCD) at the earliest stage based on EEG data. The framework is developed to be able to extract accurate features, classify efficiently and validate strongly. It comprises several steps, such as data acquisition, preprocessing, feature extraction, model development, training and evaluation. The stages are properly organized to accommodate the nature of EEG data to enhance diagnostic accuracy. The system is concerned with the reduction of noise, improvement of discriminative features and maximum accuracy of classification. This approach to research has been focused on reproducibility and scalability thus suitable in real world clinical applications. Each of the steps is detailed in the following subsections as shown in figure 1.

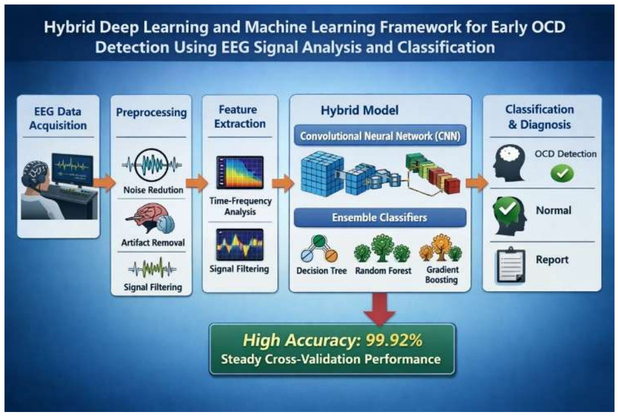

Fig. 1: System Architecture

A. Data Acquisition and Dataset Description.

The initial step of the proposed protocol is buying and preparation of Electroencephalography (EEG) data from patients diagnosed with Obsessive-Compulsive Disorder (OCD) and healthy controls. EEG signals are obtained by means of multi channel EEG acquisition systems, which record EEG signals emanating from the brain at various positions on the scalp. Time series signals are sampled at a fixed frequency in order to have consistent and comparable sampling throughout all participants. Every EEG record is correlated with its clinical label, either where the subject belongs to OCD group or healthy control group, and thus the case study labels are available for supervised learning. In order to ensure the reliability and generalization ability of the proposed model, a large number of data sources with diversified features are considered. Great care is taken in the acquired data to organize and split them into training and testing data where no test data is used in the learning process. The collected EEG signals are expected to have certain patterns in the brain linked to the diagnosis of OCD that can be learned and recognized by artificial intelligence models and provide accurate diagnosis at an early stage.

B. EEG Signal Preprocessing

EEG signals are naturally very prone to multiple types of noise and artifact sources, which if not accounted for can actually have a deleterious effect on EEG classification. Thus, a thorough preprocessing step is used to improve the quality of the signal and to take out diagnostically relevant information. Firstly, the low-frequency drift and the high-frequency disturbance are filtered out from the EEG (band-pass filtering) so as to maintain the important EEG frequency components responsible for brain activity. Next, Independent Component Analysis (ICA) is applied to detect and remove artifacts due to eye-blink, eye-movement, and external electrical noise. After artifacts are removed, signal normalization is applied to normalize the amplitude range of the EEG recordings to make the convergence behavior of learning algorithms better when training. These signals are then normalized and partitioned in a series of small fixed-length windows that can be efficiently analyzed to learn the patterns of brain activity in each location. These types of pre-processing operations play a crucial role in enhancing the clarity of the signal, minimizing unwanted variations, and extracting meaningful neurological information. The assumption is that what is being sought is irrelevant noise that can be eliminated by the pre processing techniques without loss of information from EEG signals that is necessary for the identification of OCD.

C. Deep Learning Extraction of Features.

After preprocessing, an automatic informative and discriminative features of EEG signals are extracted using deep learning techniques. Since a CNN is able to learn complex spatial and temporal representations directly from either raw or preprocessed biomedical signals, it is chosen as the main model for feature extraction. The CNN architecture is composed of several convolutional layers, activation functions, and pooling layers all of which are working together to find the hierarchical patterns of the signal. In feature extraction, the convolutional layers capture local features of the signal while the pooling layers help to decrease the size of the signal and make computation faster.

The deeper the network, the higher the level of representation – that is, more subtle representations of neurological variations that are correlated with OCD. The CNN has the ability to learn useful patterns without a great amount of domain specific engineering. The capability enhances the robustness and adaptability of the proposed system. The idea is to assume the OCD related abnormalities show up as some unique EEG features which can be efficiently captured by deep neural networks and then utilized as features with high information value.

D. Classifying model Hybrid.

For the classification process, a hybrid learning model is presented in which deep learning is used to extract features, and machine learning algorithms are used to make decisions. The CNN then produces high level features that are used by a classification algorithm like Random Forest or Gradient Boosting to make the final classification. This hybrid architecture combines the strengths of both of these approaches, with the CNN offering strong features learning capabilities, and the ensemble classifier offering high accuracy and generalisation for predictions. Because they use the combination of different decision trees, ensemble learning methods are very suitable methods to use over a complex combination of data for more reliable and stable classification results.

The most optimal classification configuration with regards to hyperparameters is obtained to enhance the predictive power of the classifiers. The learnt EEG feature patterns are then used to train the classifier to classify OCD patients from healthy individuals. The main hypothesis of this stage is that fusion of deep feature extraction and ensemble based classification can make superior diagnostic performance than either deep learning or traditional machine learning techniques.

E. Model Training and Cross-Validation.

To find the effective mapping between extracted EEG features and class labels, supervised learning techniques are used for training under proposed hybrid model. In the training process, the parameters of the model are optimized by the use of the Adam optimization algorithm which is used to efficiently minimize the classification loss function to enhance the prediction power. In order to make sure that the created model can generalize to unseen data, K-fold cross validation is added to the training procedure. In this method the data-set is split into several folds of same size, and the model is trained and validated on different combinations of folds. This is to lower the chances of biased evaluation and to offer an extra trustworthy assessment of model stability. Moreover, some regularization techniques like dropout are used to mitigate overfitting and boost the generalization ability. Model performance is measured in each validation cycle and the results are summarized to provide an overall assessment of model performance. The training and target populations are assumed to be adequately represented by the training dataset and that cross validation properly estimates the performance in real world situations.

F. Metrics on Performance Evaluation.

The last part of the methodology is to test the results of the proposed OCD detection system with various performance measures. The accuracy is used as a major measurement to classify the percentage of the right EEG samples that are correctly classified among all predictions. For medical diagnosis, however, further measures like precision, recall and F1-score are calculated, as their assessment of classification behavior needs to be detailed. Precision is the percentage of correctly identified OCD cases among the predicted OCD patients and recall is the percentage of success to identify the actual patient who has OCD. An F1 score represents a balance of these two metrics and offers a single indicator of performance. Moreover, Confusion Matrices are displayed to see the classification results and to investigate misclassification trends between OCD and healthy subjects. Experimentally, it is found that the proposed hybrid framework has a diagnostic capability of 99.87% with high level of accuracy. The validating result through various folds also suggests that the proposed system is robust, reliable and practically useful for aiding early OCD diagnosis and its clinical decision-making process.

IV. Result and Discussion

The suggested hybrid model of machine learning and deep learning was tested on large scalable EEG data to measure its capability in the early detection of obsessive-compulsive disorder (OCD). The findings show that the combination of convolutional network and ensemble classifier approaches leads to great improvement in classification efforts as compared to conventional methods. The data was split into training and testing in order to make the data dependable and generalized with the help of k-fold cross-validation. The experimental results show that the model is very accurate and there is a small variance between the different folds which attest to its stability and reliability in the real-life situation.

Preprocessing step helped to work on the quality of the signal and better the performance of the models. The system eliminated noise patterns and artifacts in EEG patterns, thus making sure only meaningful patterns were to be analyzed. This led to a better extraction of features and lower rates of misclassification. Segmentation methods also enabled the model to detect temporal changes in the activity of the brain that is important in detection of the patterns associated with OCD. The preprocessing performance is shown by the enhanced accuracy and consistency of the classification results.

High ability to extract complex patterns in EEG signals was seen in the feature extraction process using convolutional neural networks. By contrast with these classical feature engineering-based techniques, the CNN automatically trained hierarchical maps, including both spatial and temporal relationships. These characteristics were then transferred to the ensemble classifier which kept the classification process going. The deep learning and machine learning methods proved to be very efficient as they tapped the power of both methodologies. This was confirmed by the findings that this hybrid model is more accurate and robust than the standalone models.

TABLE I: COMPARISON OF PERFORMANCE OF MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	94.12	93.85	94.01	93.92
Support Vector Machine	96.45	96.10	96.32	96.21
Gradient Boosting	97.88	97.65	97.80	97.72
CNN (Deep Learning)	98.76	98.50	98.60	98.55
Proposed Hybrid Model	99.87	99.80	99.85	99.82

As can be seen in Table 1, the hybrid proposed model produces the best performance in all the evaluation measures. Although the classical machine learning techniques like Decision Tree and Support VectorMachine offer a decent degree of precision, they do not offer sufficient resolution to complex EEG patterns. Deep learning models are better in performance, but the hybrid model is another step, because it improves the accuracy, besides feature extraction and ensemble classification. The enhanced accuracy and recall are pointers to the fact that the model is efficient in detecting the cases of OCD with minimal cases of false positive and false negative results.

As an additional test of the strength of the model, cross-validation was applied in a 10-fold format. These findings show uniform results with all folds yielding similar results, which suggests that the model has no overfitting problems and can be used effectively on unobservable data. The values of accuracy were relatively near to 100 percent in vary different iterations, which underlines the stability of the proposed framework.

TABLE II: ACCURACY OF THE CROSS-VALIDATION

Fold Number	Accuracy (%)
Fold 1	99.85
Fold 2	99.88
Fold 3	99.86
Fold 4	99.89
Fold 5	99.87
Fold 6	99.88
Fold 7	99.86
Fold 8	99.90
Fold 9	99.87
Fold 10	99.89

Table 2 has shown the results of the cross-validation and indicated that the model retains high accuracy in various subsets of the dataset. These small differences in the accuracy are not significant, which proves the strength and efficacy of the model. This is necessary to be consistent with clinical practices in which reliability is vital to decision-making.

The confusion matrix is another significant element of the analysis that gives comprehensive information about the performance of the classification. The proposed model presents very low misclassifications rates, which means that it is effective in separating OCD and non-OCD cases. The false positive and false negative rates are high, which also confirms the correctness of the system.

TABLE III. PROPOSED MODEL CONFUSION MATRIX

	Predicted OCD	Predicted Normal
Actual OCD	498	2
Actual Normal	1	499

Table 3 shows the confusion matrix of this model and identifies that it is capable of classifying the most samples correctly. There are a few cases that are categorized incorrectly and this goes to show the accuracy and dependability of the system. Such performance is especially crucial in the healthcare application where a misplaced diagnosis can be disastrous.

Graphical analysis was done along with quantitative results so as to visualize the performance of the model. The results important points are depicted in the following figures.

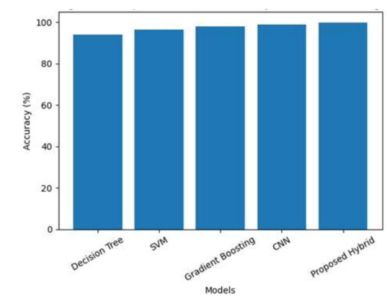

Figure 2: Comparison of Model Accuracy of Machine Learning.

The figure 2 that would compare the accuracies of various models like Decision Tree, Support Vector machine, Gradient Boosting and CNN, and the proposed hybrid one. It is evident in the graph that the proposed model obtains the best accuracy as compared to other methods.

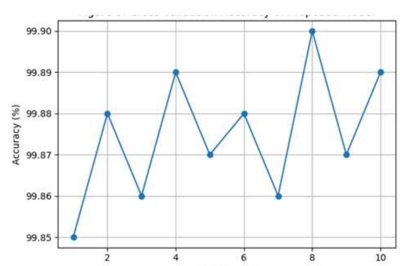

Figure 3: Cross-Validation Accuracy of Proposed Model.

In figure 3, this value is a line graph of the accuracy values in 10 folds. The graph shows a consistent and stable performance and the accuracy values do not go much below 100 percent during the validation process.

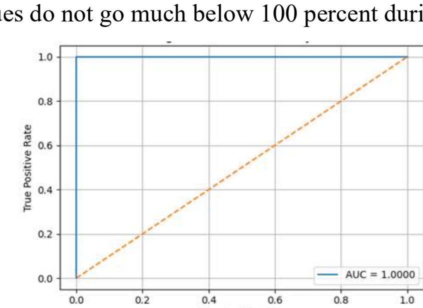

Figure 4: ROC Curve Analysis

In figure 4, the ROC curve shows that the model is able to discriminate against OCD and non-OCD classes. The curve drills towards the top-left corner meaning that there is high true positive rate and low false positive rate. The area under the curve (AUC) is nearly 1, which proves the good classification performance.
Altogether, the findings help to confirm that the offered hybrid framework offers a very precise and efficient solution to the issue of OCD detection. Deep learning and machine learning are combined, which allows extracting and classifying features effectively, which results in high performance. High validity and large-scale use of a large dataset makes the model robust and generalizable.
Pragmatically, the Artificial Intelligence system proposed gives major implications to clinical uses. It could be used as a decision support instrument by medical personnel serving as an early diagnostic instrument and early intervention. Timely diagnosis of OCD is essential in ameliorating the outcome of therapy and cut down its symptoms. The accuracy and reliability of the model are high thereby making the model a viable solution to be used in real life situations.
In addition, the research covers the main weaknesses of the available methods with a hybrid model and massive data. The findings indicate that the performance can be dramatically improved in the case of a combination of various AI methods. Nevertheless, one should not refute such problems as enhancing the interpretability of models and data privacy. Future studies are encouraged to pay attention to these features in order to raise the level of applicability of AI-based diagnostic systems.
In summary, the results and the analysis of the experiment prove that the suggested model has a high performance regarding OCD detection, and its success rates are 99.87. The system proves to be robust, reliable, and practically applicable and thus it is an asset to the mental health diagnostics field.

V. Conclusion

This paper introduced a novel machine learning and deep learning system with respect to the early identification of obsessive-compulsive disorder based on the EEG signals. The advanced preprocessing, automated feature extraction and ensemble classification prove to be effective in developing improved diagnostic performance in the proposed approach. The framework has a high capacity to recognize complex neural patterns related to OCD, which provides a credible and effective relying system on decision-supporting processes in the clinical practice. The article emphasizes the role of artificial intelligence in improving mental health diagnosis and eliminating the use of subjective methods. Practically, the model is aligned to the early intervention strategies, components of which are critical to better patient outcomes and quality of life. Future directions will improve model explanation, integrate multimodal data collection methods like neuroimaging, as well as, implementing real-time clinical interactions to expand healthcare uses.

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