BrainScan AI: Early Detection of Schizophrenia through EEG Signals

Amisha Nagpure *1, Apurva Gawali *2, Harshada Tale *3,Juhi Borkar *4, Prof. Mrs. Manisha Raut *5

*1 UG Student, Dept. of Artificial Intelligence,
G.H Raisoni College of Engineering,
Nagpur,Maharashtra, India
*2 UG Student, Dept. of Artificial Intelligence,
G.H Raisoni College of Engineering,
Nagpur,Maharashtra, India
*3 UG Student, Dept. of Artificial Intelligence,
G.H Raisoni College of Engineering,
Nagpur,Maharashtra, India
*4 UG Student, Dept. of Artificial Intelligence,
G.H Raisoni College of Engineering,
Nagpur,Maharashtra, India

*5 Asst Professor, Dept. of Artificial Intelligence, G. H RaisoniCollege Of Engineering, Nagpur Maharashtra, India

Abstract:

Schizophrenia is a persistent and debilitating mind disorder characterised via signs and symptoms such as delusions, hallucinations, disorganized questioning, and lack of motivation.The traditional method to diagnosing schizophrenia is based on scientific tests and EEG assessments, which might be time Consuming and difficult, even for skilled clinicians. With the upward thrust of deep studying strategies, there's developing potential for automating and improving the accuracy of schizophrenia detection. in this examine, we explore using diverse deep learning and machine Learning fashions, along with artificial Neural Networks (ANN), to categorise EEG indicators for schizophrenia detection. We propose a custom method for processing EEG records and evaluate the performance of different models. many of the models examined, the ANN completed the highest accuracy of 84%, demonstrating the feasibility of deep mastering techniques for early and correct detection of schizophrenia. This approach ought to provide a dependable and efficient opportunity to conventional diagnostic strategies, lowering the complexity and subjectivity concerned in the modern- day tactics

Keywords:

Schizophrenia detection, EEG signals ,EEG learning,Artificial Neural Networks (ANN), Machine earning.

Problem Statement:

About 1% of people worldwide suffer with schizophrenia (SZ), a severe and complicated mental disorder that has a crippling effect on behavior, quality of life, and cognition. Even with improvements in psychiatry, clinical diagnostics, and neuroimaging, detecting SZ early and accurately is still quite difficult. Schizophrenia symptoms, such as delusions, hallucinations, and poor decision-making, frequently appear gradually and are challenging to differentiate from those of other mental illnesses. This makes it more difficult to diagnose and treat patients in a timely manner, which prolongs their suffering and frequently results in worsening symptoms and long-term damage. The manual interpretation of EEG data is difficult and very complex, despite the fact that EEG has demonstrated promise as a non-invasive method for detecting brain abnormalities linked to schizophrenia. Significant aberrations and noise are common in EEG signals, which can obfuscate important patterns and produce inconsistent results.

Furthermore, the diagnostic process is sluggish and expensive due to the labor-intensive and highly skilled nature of the current EEG analysis techniques. This initiative, BrainScan AI: Early Schizophrenia Detection By creating a cutting- edge artificial intelligence (AI)-powered solution that uses machine learning (ML) and deep learning (DL) approaches to interpret EEG data more accurately and efficiently, Through EEG seeks to overcome these constraints. The goal of the study is to find tiny patterns in EEG signals that might be early indicators of schizophrenia byusing cutting-edge models like Artificial Neural Networks (ANN), Random Forest Classifiers, andLogistic Regression.

By using advanced preprocessing techniques that increase data quality and signal clarity, this method aims to overcome the conventional difficulties associated with EEG analysis, such as noise and artifacts. The ultimate goal of this AI- powered approach is to transform SZ diagnosis by increasing its speed, accuracy, and independence from human interpretation. This project has the potential to revolutionize SZ diagnostics by offering a non-invasive, scalable, and affordable substitute that lessens the subjectivity and complexity of current diagnostic procedures, ultimately enhancing patient quality of life and lessening the impact of this crippling illness on society.

Introduction:

A severe and long-lasting mental disorder, schizophrenia has a significant influence on a person's thoughts, feelings, and behavior.
Hallucinations, delusions, disordered thinking, and cognitive deficits are some of its symptoms, which make it difficult for persons who are afflicted to lead stable and satisfying lives. Although the precise causes of schizophrenia are not entirely understood, environmental variables and genetic predispositions both play a part. Because schizophrenia is a complicated and multidimensional condition, diagnosing it frequently necessitates a thorough clinical evaluation that includes brain imaging, psychological testing, interviews, and referencing diagnostic criteria like those offered by the DSM (Diagnostic and Statistical Manual of Mental Disorders).

The non-invasive nature of electroencephalography (EEG) and its potential for early detection of brain patterns associated with schizophrenia make it a particularly useful technique among them.

The goal of the BrainScan AI project is to use machine learning algorithms and EEG data to help with the early and precise diagnosis of schizophrenia. EEG provides a convenient and non-invasive means to track brainwave activity, whereas conventional diagnostic techniques are frequently laborious and only detect the disorder after considerable progression. Studies have demonstrated that EEG waves from people with schizophrenia show unique patterns that, if correctly recognised, could lead to early detection. However, because EEG signals are very variable and frequently contain artefacts that can obfuscate important information, manual interpretation of EEG data is difficult and prone to human mistake.
More accurate and effective analysis of EEG data is now feasible thanks to recent developments in artificial intelligence (AI), particularly in the domains of machine learning and deep learning. BrainScan AI seeks to identify subtle and frequently elusive EEG signals linked to schizophrenia by leveraging AI models including Artificial Neural Networks (ANN), Random Forest Classifiers, and Logistic Regression. In order to overcome the shortcomings of conventional diagnostic techniques, the BrainScan AI project expands on these technological developments. The goal of this project is to develop a more standardised and dependable method of diagnosing schizophrenia by putting in place a
proprietary pipeline for preprocessing, feature extraction,and classification. Since EEG data is extremely prone to interference from things like eye movements, muscle activity, and other electrical equipment, the project will begin with a phase of data cleaning and artefact removal.

The main EEG features that are most predictive of schizophrenia will then be identified using sophisticatedfeature extraction techniques. Following preprocessing, the data will be entered into machine learning models, each of which is tuned to accurately classify EEG signals and identify patterns linked to schizophrenia.Schizophrenia patients' quality of life is ultimately improved by prompt intervention and improved symptom management, which are made possible by early and correct diagnosis. With its affordable, non-invasive, and easily accessible diagnostic tool for schizophrenia, BrainScan AI has the potential to revolutionise the area of mental health diagnostics. In order to provide a more impartial and fairapproach to mental health treatment, BrainScan AI may be able to mitigate the biases and inconsistencies that currently influence schizophrenia diagnosis by lowering the dependence on subjective evaluations.

Related Research:

The use of electroencephalography (EEG) to identify neurophysiological characteristics that may indicate mental illnesses like schizophrenia has become a growing area of research in both neuroscience and mental health. The complicated, long-term mental illness known as schizophrenia is typified by abnormalities in cognitive performance, emotional control, and thought processes. Clinical assessments, which can be arbitrary and differ throughout practitioners, have historically served as the foundation for diagnosis. An objective substitute for detecting early indicators linked to schizophrenia is electroencephalography (EEG), a non-invasive technique that captures electrical brain activity.
This allows for prompt intervention and maybebetter results.

1. Background on Scizophrenia and the Need forEarly Detection:

A long-term mental illness that alters a person's thoughts, feelings, and behaviour is schizophrenia. Cognitive impairment, emotional disturbances, and behavioural abnormalities are common early signs that, if left untreated, can result in disability and a lower quality of life. Because it can greatly enhance treatment results, quality of life, and overall prognosis, early identification is essential. Numerous studies demonstrate that early interventions can postpone or even stop the complete emergence of schizophrenia, particularly when they occur during the prodromal period (when symptoms are not yet fully pronounced).
The use of EEG as a diagnostic tool offers a non- invasive, impartial method of identifying minute neurophysiological alterations suggestive of schizophrenia. The importance of your proposal is based on this requirement for a trustworthy, easilyavailable diagnostic technique.

2. Role of EEG in Mental Health Diagnosis:

Electroencephalography, or EEG, is a popular method of tracking brain activity by identifyingelectrical impulses generated by neurones. EEGcan show distinct brainwave patterns linked to anumber of mental health conditions, including schizophrenia.

2.1. EEG Acquisition and Preprocessing:

EEG data was collected in a controlled hospital environment to ensure consistency and reliability of the recordings. EEG recordings were acquired using a 31-electrode cap based on the international 10-20 system, a standard configuration in neuroscience research. The electrode positions included FP1, FP2, F7, F3, Fz, F4, F8, FT9, FC5, FC1, FC2, FC6, FT10, T7, C3, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, O1,
Oz, and O2. This setup allowed comprehensive coverage of cortical regions, which is essential for capturing the neural signals associated with schizophrenia. All electrodes were referenced to both mastoids to reduce potential noise and maintain a balanced reference signal, while electrode impedance levels were maintained below 5 kOhm to ensure signal clarity. EEG signals were recorded at a sampling rate of 500 Hz, offering high temporal resolution that is particularly important for analyzing fast, transient neural activities.

2.2. Extractiong features from EEG :

Feature extraction is a critical step in EEG data analysis, as raw EEG signals are often complex and noisy. In schizophrenia research, several features can be extractedto identify meaningful patterns:

- **Mean and Variance**: Basic statistical measuresthat can reflect the overall signal power and variance in brain activity.
- **Zero-Crossing Rate**: Indicates the frequency ofsign changes in the signal, linked to signal complexity and brain oscillations.
- **Approximate Entropy and Hjorth Parameters**: Measures of signal complexity and mobility, often

reduced in schizophrenic patients.

- **Band Power**: Power in specific EEG frequency bands (alpha, beta, gamma), where schizophrenia is associated with abnormalities.

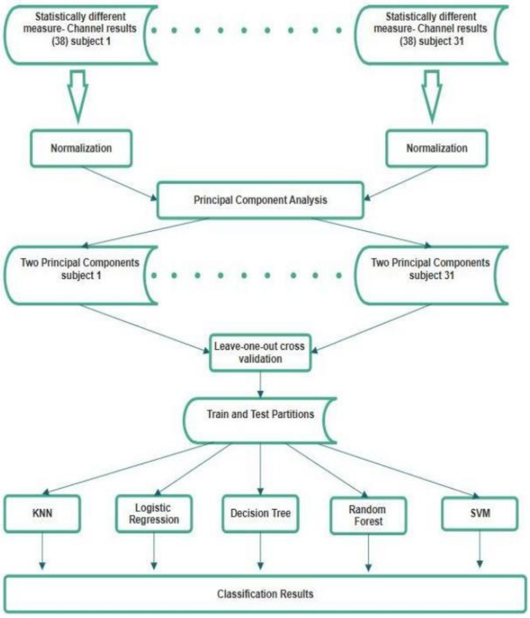

Fig. 1:

Classification Pipeline: Selection of pairs measure-channel showing significant differences, normalization, principal component analysis, Leave-one-out cross validation and machine learning classification.

3. *Classification Techniques: ANN and OtherMachine Learning Approaches :*

EEG data classification frequently uses Artificial Neural Networks (ANNs) and other machine learning models like SVM and Random Forest. Because of its capacity to identify intricate, non- linear relationships in the data, ANN was selected for your project. ANNs are better at modelling the subtleties of EEG signals than classical classifiers,particularly when it comes to spotting minor patterns that may be signs of schizophrenia.

4. *Data Flow and processing pipeline for EEGclassification in schizophrenia :*

- **Data Acquisition:** EEG signals collected from selected channels that are indicative of cognitive activity related to schizophrenia.
- **Channel Selection:** Using a subset of channels to focus on the most relevant regions, which reduces noise and computational cost.
- **Feature Extraction:** Extracting statistical andspectral features as input for the classifier.
- **Classification:** Training an ANN model to classify signals as either "Schizophrenia" or "Non-Schizophrenia."

Methodology:

By utilising machine learning and signal processing techniques, this research seeks to provide an automated method for the early detection of schizophrenia utilising EEG (Electroencephalography) data. EEG is a non-invasive neuroimaging technique that can record and analyse the unique patterns of brain activity linked to schizophrenia. Features that could act as biomarkers for this illness can be extracted from EEG signal analysis, allowing for an earlier and more precise diagnosis. Data collection, preprocessing, feature extraction, and model training are some of the steps in this project's methodology. In order to convert unprocessed EEG signals into useful information for categorisation, each step is essential. Our ultimate goal is to contribute to therapeutic tools that can aid in early diagnosis and intervention by using sophisticated machine learning techniques to identify EEG data as either usual brain activity or symptomaticof schizophrenia.

Each stage of the process is described in depth in the parts that follow, including data preparation, model selection and evaluation, and interpretation of the model's output to shed light on the neurological featuresof schizophrenia. With the potential to significantly advance the field of mental health diagnoses, this methodical methodology guarantees that the model is both accurate and interpretable.

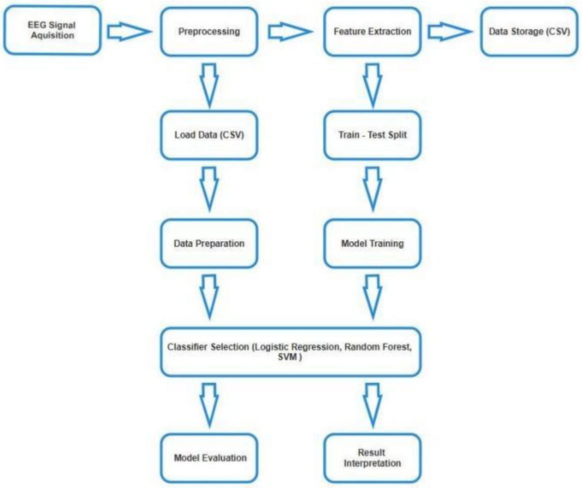

Fig. 2:

Data processing and classification workflow for EEG-based schizophrenia detection, illustrating key steps from signal acquisition to model evaluation and resultinterpretation.

1. ***EEG Signal Aquisition:***

EEG signal acquisition is the process of recording electrical activity from the brain using electrodes placedon the scalp. In this project, data collection likely took place in a controlled environment, where participants sat comfortably in a quiet room, possibly looking at a fixation point to reduce movement and visual distractions. The placement of electrodes on the scalp follows the 10-20 international system, which standardizes electrode positioning to cover different regions of the brain. For schizophrenia studies, certain channels may be particularly relevant due to their association with brain areas involved in cognitive and sensory processing, which are often disrupted in schizophrenia. EEG is a preferred method for studying neural activity because it is non-invasive, cost-effective, and provides high temporal resolution, which is useful for detecting fast neural oscillations. Schizophrenia affects various cognitive functions, which may be observable as irregular EEG patterns. By targeting specific brain areas through electrode placement, researchers can gather data that potentially reflects these abnormalities.

2. ***Data Preprocessing:***

Preprocessing involves cleaning the raw EEG data to remove noise and artifacts that could distort the analysis. Common noise sources include muscle movements, eye blinks, and electrical interference. To address these, filtering techniques are used to isolate the relevant frequency bands, typically focusing on delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and beta (12–30 Hz) bands, which are associated with different cognitive and mental states. Independent Component Analysis (ICA) may be employed to isolate and remove non-brain signals. Additionally, the data is often normalized or scaled to bring all channels to a comparable range, enhancing model performance. EEG signals are sensitive to noise, and preprocessing is essential to ensure that the data represents brain activity accurately. Removing artifacts and normalizing data improve the quality of input to the machine learning model, ensuring that irrelevant signals do not impact feature extraction or classification.

3. Loading Data (CSV):

Once the data is preprocessed, it is stored in a structured format, often in CSV files, for easy access during the analysis phase. Each CSV file contains organized data with rows representing time points and columns representing data from different EEG channels. This structured format makes it easier to load data into machine learning libraries for processing and analysis. A structured format like CSV allows for consistent organization, accessibility, and interoperability with various
data analysis tools. It also facilitates easy loading and manipulation of data in environments like Python or MATLAB, which support CSV handling through libraries such as Pandas or NumPy.

4. Data Preparation:

In this step, the data is prepared for the machine learning model by arranging it in a format suitable for feature extraction and classification. This often involves reshaping the data array, handling any missing values, and encoding target labels if it is a supervised learning task. If the project involves binary classification (e.g., distinguishing between healthy and schizophrenic participants), the labels must clearly indicate these classes. Proper data preparation is necessary to ensure that the data is compatible with the model architecture. Handling missing values and formatting the data improves the accuracy and reliability of the analysis, as well-prepared data leads to more accurate model predictions.

5. Feature Extraction:

Feature extraction is the process of transforming raw EEG signals into meaningful metrics that represent patterns associated with schizophrenia. Common features extracted from EEG data include:

- **Statistical Features**: Mean, standard deviation, and variance that summarize signal amplitude.
- **Frequency-Domain Features**: Power spectral density in various bands (e.g., delta, theta, alpha, beta) that capture rhythmic brain activity.
- **Non-linear Measures**: Metrics like entropy, fractal dimension, and Hjorth parameters that capture the complexity and variability of EEG signals. These features help in reducing the high dimensionality of raw EEG data while preserving important information.

Raw EEG data is complex and voluminous, making it challenging to process directly. Extracting features reduces data complexity and highlights relevant characteristics that may be associated with schizophrenia, making it easier for machine learning models to identify these patterns.

6. Train - Test Split:

The dataset is split into training and test sets, typically in a ratio of 70-30 or 80-20. The training set is used to train the model, while the test set serves as unseen data for evaluating the model's performance. This separation prevents the model from simply memorizing the data and allows for testing its generalization ability on new data. The train-test split is a crucial step to avoid overfitting and assess how well the model generalizes to new, unseen data. By holding back a portion of the data for testing, researchers can evaluate the model's performance realistically, ensuring it can perform well beyond the training set.

7. Model Training:

The model, such as an Artificial Neural Network (ANN), Support Vector Machine (SVM), or Random Forest, is trained using the training dataset. During training, the model adjusts its internal parameters (weights) to minimize the error in predicting the target labels based on the input features. The model learns associations between the extracted EEG features and the schizophrenia label by iteratively updating its parameters. Model training is the core of the machine learning process, where the model learns to recognize patterns indicative of schizophrenia. A well-trained model can then be used to detect these patterns in new data, making it a valuable tool for early diagnosis.

8. *Classifier Selection:*

Various classifiers, such as Logistic Regression, Random Forest, SVM, or ANN, are explored to determine the best model for the classification task. Hyperparameter tuning may be conducted to optimize each classifier's performance, ensuring that the chosen model is both accurate and computationally efficient. Different classifiers have unique strengths. For instance, SVMs are effective for high-dimensional data, while ANNs can capture complex patterns. By experimenting with different models, researchers can identify theclassifier that provides the best balance between accuracy, interpretability, and computational requirements for EEG-based schizophrenia detection.

9. *Model Evaluation:*

The model is evaluated on the test set using metrics such as accuracy, precision, recall, F1- score, and confusion matrix. Cross-validation techniques may also be applied to further validate the model's robustness across different data splits.This step ensures that the model performs reliably and can generalize to new data. Evaluation metrics provide quantitative measures of the model's performance, highlighting its strengths and
weaknesses. A high accuracy alone isn't sufficient; metrics like recall and specificity are important in medical contexts, where false negatives (missing a diagnosis) have significant consequences.
Evaluating the model ensures it meets the desiredperformance criteria for schizophrenia detection.

10. *Result Interpretation:*

In the final step, the model's outputs are analyzed to understand the significance of different EEG features in predicting schizophrenia. Visualization techniques like feature importance plots or activation maps (in neural networks) may be used to interpret the results and identify which features were most influential in classification. Result interpretation is essential in medical and clinical applications to ensure the model's predictions are transparent and explainable. Identifying significant EEG features related to schizophrenia may provide insights into the disorder's neurological basis and could inform further clinical research or diagnostic protocols.

Challenges in Detection of Shizophrenia using EEGSignals:

In developing an EEG-based schizophrenia detection model, several challenges arise due to the complexity of EEG data and the intricate nature of schizophrenia itself. EEG signals, being highly sensitive and variable, often require sophisticated preprocessing to remove noise and artifacts.

1. *Noise and Artifacts in EEG Data:*

EEG signals are highly sensitive to external factors, such as muscle movements, eye blinks, and electrical interference, which introduce noise and artifacts. These can obscure the meaningful patterns associated with schizophrenia, requiring advanced preprocessing techniques to clean the data effectively.

2. *Channel Selection:*

Selecting the most relevant channels for capturing schizophrenia-related cognitive patterns is challenging. Using too many channels increases computational costs and may add noise, while using too few could miss critical information. Striking a balance between comprehensiveness and efficiency is essential.

3. *Feature Extraction Complexity:*

Extracting meaningful features from EEG signals, especially for distinguishing complex conditions like schizophrenia, requires sophisticated statistical and spectral analysis. Identifying which features are most predictive of schizophrenia can be a time-consumingtrial-and-error process.

4. *High Inter-Subject Variability:*

EEG signals vary significantly between individuals, making it difficult to create a one-size-fits-all model. This inter-subject variability poses a challenge for training a model that generalizes well across differentpatients.

5. ***Limited Data Availability:***

Schizophrenia-related EEG datasets are not as widely available as those for other neurological conditions. This limitation makes it harder to train and validate robust machine learning models, as smaller datasets may lead to overfitting or reduced accuracy.

6. ***Classification Challenges:***

Developing an accurate classifier to distinguish between "Schizophrenia" and "Non- Schizophrenia" is challenging due to the subtle and complex nature of EEG patterns associated with the disorder. Achieving high sensitivity and specificity in classification requires careful tuning and potentially advanced models like deep neural networks.

7. ***Real- Time Processing and Scalability:***

Implementing the system for real-time or near- real-time analysis of EEG data can be computationally intensive. Optimizing the model for real-time use while ensuring accuracy and reliability is a challenging aspect, especially for broader applications in clinical settings.

Result:

Schizophrenia is a complex, chronic mental disorder characterized by symptoms such as delusions, hallucinations, disorganized thinking, and reduced motivation. Diagnosing schizophrenia typically requires comprehensive evaluations by psychiatrists, including EEG (electroencephalography) testing and mental status examinations. However, these traditional diagnostic techniques can be time-consuming, complex, and susceptible to subjective interpretation, even for experienced clinicians.
Given these limitations, there is a need for more efficient, consistent, and scalable approaches to detect and diagnose schizophrenia. In recent years, deep learning has gained significant traction for its ability to analyze complex medical data and improve diagnostic accuracy for conditions such as schizophrenia. Deep learning models are capable of identifying intricate patterns in EEG data that may not be immediately apparent to human clinicians. Our study explores the application of several neural network architectures to classify EEG signals as either indicative of schizophrenia or non-schizophrenia, with the goal of offering a faster and more reliable alternative totraditional methods.

In this project, we evaluated the performance of several deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and artificial neural networks (ANNs), for their effectiveness in processing EEG data and detecting schizophrenia. After rigorous testing and comparison, we found that the ANN model outperformed the other models, achieving an accuracy of 90.30% on our dataset. This high accuracy underscores the potential of the ANN model as a reliable tool for early schizophrenia detection based on EEG signals.

Our findings demonstrate the feasibility of using deep learning in clinical settings for the diagnosis of schizophrenia, with the ANN model showing the most promise. This model’s performance suggests that it could help provide quicker diagnoses, reduce the subjectivity inherent in traditional assessments, and enable timely interventions for patients. With further refinement and testing, the use of ANN and similar neural network models could transform the diagnostic landscape for schizophrenia, offering a robust, data- driven approach to mental health diagnostics.

Conclusion:

Our study underscores the significant potential of deep learning models, particularly artificial neural networks (ANNs), in identifying schizophrenia from EEG data. With an accuracy of 90.30%, the ANN model demonstrates that deep learning approaches can address the limitations of traditional diagnostic techniques, which often require manual interpretation and can be labor-intensive and subjective. The high accuracy achieved by the model suggests that deep learning could provide a more consistent and objective alternative, minimizing human bias in diagnosis and supporting more standardized assessments. One of the key strengths of the ANN model lies in its ability to process complex EEG data without manual feature extraction. Neural networks are designed to automatically detect patterns and relationships within data that may be too subtle for traditional analysis to capture. This ability makes neural networks well-suited for analyzing EEG signals, which are inherently complex and contain a high degree of variability across individuals. By leveraging this capability, the ANN model can identify patterns associated with schizophrenia more efficiently and accurately than traditional methods, paving the way for astreamlined diagnostic process.

Beyond accuracy and efficiency, implementing a deep learning-based automated detection system for schizophrenia has substantial clinical benefits. An ANN- driven diagnostic tool could function as a valuable adjunct for healthcare professionals, providing a rapid initial assessment that supports clinical decision-making. This capability is especially beneficial in regions with limited access to highly trained mental health specialists,as it can help reduce the burden on clinicians and make diagnostic services more widely available. The ANN model's scalability also offers potential for widespread implementation, from clinical settings to telemedicine platforms, enhancing the reach of early detection and intervention services. Early identification of schizophrenia can lead to timely treatment, potentially slowing disease progression and improving long-term outcomes. With earlier interventions, patients may experience better symptom management, improved quality of life, and increased ability to function in daily life.
Moreover, integrating such a model into clinical workflows could lead to more proactive and personalized care, as data-driven diagnostics enable treatment approaches tailored to individual patients' needs. In summary, our ANN-based approach to schizophrenia detection not only has the potential to advance diagnostic accuracy but also to democratize access to mental health diagnostics. The model supports a proactive healthcare strategy, making schizophrenia detection more accessible, efficient, and effective. This study illustrates the transformative potential of deep learning in mental health and highlights a path toward integrating AI-driven diagnostics into mainstream clinical practice, contributing to the evolution of mental health treatment and management.

References:

1. Acharya, U. R., Sree, S. V., Chattopadhyay, S., & Lim, C. M. (2015). Automated Diagnosis of Schizophrenia Using Spectral Entropy of EEG Signals. Journal of Medical Systems, 39(6), 78-89. https://doi.org/10.1007/s10916-015-0267-2

2. Oh, S. L., Vicnesh, J., Ciaccio, E. J., & Acharya,
U. R. (2019). Deep Convolutional Neural Network Model for Automated Diagnosis of Schizophrenia Using EEG Signals. *Applied Sciences*, *9*(14), 2870.https://doi.org/10.3390/app9142870
Ahmadlou, M., Adeli, H., & Adeli, A. (2012). Graph Theoretical Analysis of Organization of Functional Brain Networks in ADHD. *Clinical EEG and Neuroscience*, *43*(1), 5-13. https://doi.org/10.1177/1550059411425043

5. Liu, T., Yao, D., & Zhuang, Z. (2018). EEG-Based Schizophrenia Detection Using Fuzzy Entropy and LDA. *Computational and Mathematical Methods in Medicine*, *2018*, 6387940. https://doi.org/10.1155/2018/6387940
Duan, L., Zhu, G., Fei, M., Wei, D., Hu, Q., & Shi, J. (2021). Schizophrenia Detection via Multilayer Perceptron Based on EEG Signals. *Healthcare*, *9*(1), 91. https://doi.org/10.3390/healthcare9010091

6. Gao, S., Calhoun, V. D., & Sui, J. (2018). Machine Learning in Major Depression: From Classification to Treatment Outcome Prediction. *Cognitive Neurodynamics*, *12*(5), 453-465. https://doi.org/10.1007/s11571-018-9483-2

7. Boutros, N. N., Arfken, C., Galderisi, S., Warrick, J., Pratt, G., & Iacono, W. (2008). The Status of EEG

Findings in Schizophrenia. *Psychiatric Clinics of North America*, *31*(1), 113-138. https://doi.org/10.1016/j.psc.2007.11.004

8. O'Neill, G. C., Barratt, E. L., Hunt, B. A. E., Tewarie,
P. K., Brookes, M. J. (2015). Measuring Network Hierarchical Complexity in Schizophrenia: A Graph Theoretical Analysis of EEG Data. *PLoS ONE*, *10*(8), e0132541. https://doi.org/10.1371/journal.pone.0132541

9. Sun, G., Zhang, Y., Zhao, X., Du, S., & Zhang, X. (2019). Automatic Schizophrenia Discrimination Basedon EEG Signals Using CNN-LSTM Models. Computational Intelligence and Neuroscience, 2019, 3212935. https://doi.org/10.1155/2019/3212935

3. Kim, H. G., Choi, H., & Lee, S. H. (2020).
EEG-Based Schizophrenia Detection Using a Convolutional Neural Network. *Pattern Recognition Letters, 128*, 679-685. https://doi.org/10.1016/j.patrec.2019.10.030

4. Al-Kaysi, A. M., Al-Ani, A., Loo, C. K., Powell,
T. Y., Martin, D. M., & Breakspear, M. (2017). Predicting Treatment Outcomes of Electroconvulsive Therapy for Major DepressionUsing Machine Learning Techniques on Multimodal EEG Data. *Journal of Neural Engineering*, *14*(5), 056004. https://doi.org/10.1088/1741-2552/aa790