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| RESEARCH ARTICLE

EEG Functional Connectivity and Deep Learning for Automated Diagnosis of Alzheimer's disease and Schizophrenia

Mohammad Hasan Sarwer[1], Tui Rani Saha[2], Shake Ibna Abir[3]✉, Shaharina Shoha[3], Md Miraj Hossain[4], Nigar Sultana[5], Shariar Islam Saimon[6], Intiser Islam[6], Mahmud Hasan[7], Sarder Abdulla Al Shiam[8], Rafi Muhammad Zakaria[9]
[1]Department of Business Administration-Data Analytics, University of New Haven, CT, USA
[2]Department of Business Administration-MBA, University of New Haven, CT, USA
[3]Instructor of Mathematics, Department of Mathematics and Statistics, Arkansas State University, Arkansas, USA
[4]Department of Computer Science, West Chester University, Pennsylvania, USA
[5]Department of Finance, University of New Haven, CT, USA5
[6]Department of Computer Science, School of Engineering, University of Bridgeport, USA
[7]Department of Cybersecurity, ECPI University, Virginia, USA
[8]Department of Management–Business Analytics, St Francis College, New York, USA
[9]Department of Management Science and Information Systems, University of Massachusetts Boston, Boston, USA
Corresponding Author: Shake Ibna Abir, **E-mail**: sabir@astate.edu

| ABSTRACT

Electroencephalogram (EEG) functional connectivity analysis provides important clues about brain network abnormalities, an important approach to diagnose complex neurological diseases such as Alzheimer's disease and schizophrenia. Advanced computational analysis can effectively analyze disorders with unique disruptions in neural connectivity. Deep learning (DL) is one of these, and has emerged as a powerful tool to facilitate automation in diagnostic processes and accurate classification by the use of DL models. The application of DL techniques and EEG functional connectivity metrics for the automated diagnosis of Alzheimer's disease and schizophrenia is investigated in this study. For analysis, EEG data from patients with these disorders were used. To quantify the interregional synchronization of neural activity, functional connectivity metrics, such as coherence and phase locking value were extracted. Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM) networks based multi class classification framework was designed to detect patterns related with the disorders. Results demonstrated DL framework performance at 94% for Alzheimer's disease and 91% for schizophrenia. The DL models were then found to robustly replicate such inter-regional disruptions, with connectivity patterns analyzed via connectivity maps, revealing distinct inter-regional patterns in both conditions. This has also been demonstrated by the superior performance of DL methods in processing EEG data with complex and high dimensionality, and in extracting informative features for diagnosis. Finally, EEG functional connectivity metrics and DL methods greatly increase diagnostic accuracy for Alzheimer's disease and schizophrenia. These findings point towards the transformative power of AI driven solutions in clinical diagnostics to achieve scalability and efficiency in neurological disorder diagnosis. Future research should be directed towards gap expanding application level of these models to other neurological conditions, and refinement of frameworks that can be implemented in a clinical setting.

| KEYWORDS

EEG functional connectivity, neurological diseases, Alzheimer's disease, schizophrenia, deep learning, convolutional neural networks, long short-term memory, diagnostic automation, coherence metrics, phase locking value.

| ARTICLE INFORMATION

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1. Introduction

1.1 The Global Challenge of Neurological Disorders

Neurological disorders Alzheimer’s disease (AD) and schizophrenia (SZ) emerge as critical health issues worldwide because they harm millions of sufferers and overwhelm medical resources. Alzheimer's disease causes brain cells to break down as it makes people first struggle with their memory and then become unable to take care of themselves without help. Schizophrenia presents as a severe mental illness that produces delusions and hallucinations while causing patients to think in disorganized patterns and suffer brain power loss according to Loch 2019 findings. The brain issues and disorganized neural functions found in both conditions make professional diagnosis hard especially when they first emerge despite their different symptoms. Scholars need well-designed diagnostic solutions now more than ever because these sophisticated tools can solve the current diagnostic problems when evaluating complex brain conditions.

1.2 EEG as a Window into Brain Connectivity

EEG technology now serves as an effective non-invasive way to track how brain networks communicate with each other. Through EEG measurements of brain electrical signals scholars can study how neurons coordinate brain function according to Babiloni et al., 2020. Measuring how brain regions work together reveals the abnormal connections in brains affected by neurological disorders. Scientists measure brain connections using coherence and PLV methods to understand how network activity differs in people with AD and SZ. The evaluation of EEG data stays complicated due to its detailed data structure, changing signals over time and hidden patterns within.

1.3 The Role of Deep Learning in EEG Analysis

Deep learning technology transforms how scholars analyze data in every sector especially healthcare. DL uses smart AI setups to process neural networks for finding important data points that beat older machine learning ways according to Taye's 2023 findings. Through deep learning technology engineers can automate EEG studies with high precision and work with large datasets to find complex signal patterns that standard methods miss. CNNs and LSTM networks effectively extract essential information from EEG data which improves classification results and boosts diagnostic performance of different brain disorders.

1.4 Objectives and Scope of the Study

The research uses deep learning methods to analyze brain connectivity patterns from EEG data for identifying Alzheimer’s disease and schizophrenia. This research links the measurable patterns found in functional connectivity data to deep learning models that detect patterns and classify results to fix existing problems in diagnosis methods. The research extracts coherence and PLV functional connectivity data using EEG measurements from established AD and SZ patient cases. The research team uses deep learning with CNN and LSTM models to study the extracted functional connectivity data. The findings demonstrate that the AI system can correctly identify Alzheimer's disease in 94% and schizophrenia in 91% of cases proving that this automated diagnostic approach can revolutionize clinical assessments.

1.5 Insights and Contributions

This study shows how important analyzing brain connections are to understand how neurological disorders affect brain function. Theconnectivity maps show different patterns of brain region disruptions that illuminate the scientific basis for both Alzheimer's and Schizophrenia. The study results demonstrate that connectivity analysis improves diagnosis precision and expands disease knowledge which helps create specific treatment plans for each patient (Singh et al., 2023).

1.6 Challenges and Future Directions

The progress made in this research presents important technical hurdles that need overcoming before practical implementation. Thestudy shows that DL models require more research to work properly across different patients while needing bigger and balanced data sets along with clearer explanations of neural network results (Alzubaidi et al., 2024). Using these technologies in everyday healthcare settings requires evaluation of processing needs as well as ethical and system preparedness factors. Research proves that using deep learning with EEG functional connectivity provides a powerful automated diagnosis tool for Alzheimer's and schizophrenia that works well at scale and produces precise results (Dixit et al., 2023).

The first section of this study reviews research about EEG functional connectivity to show how it helps diagnose Alzheimer's disease and schizophrenia. The methods section explains how scholars collected and processed EEG data to prepare it for analysis and then developed the deep learning system. This section shows study outputs including deep learning model success rates and the knowledge gained from neural connectivity analysis. The paper continues by examining what the results mean as well as research boundaries and proposes new study directions. The final part of this paper reviews the important discoveries made and assesses how this research will affect medical and neuroscience studies.

2. Literature Review

2.1 EEG Functional Connectivity

Both scientific research and brain scans using EEG help us better understand how brain networks behave in people with neurological disorders. Du, Fu, and Calhoun's 2018 study shows that analyzing brain connection patterns helps detect brain disorders and tracks how neural networks become disconnected. However they point out the basic limitations when working with multifaceted brain data. Babaeeghazvini and team (2021) show through their research on MRI and EEG combination that brain disorder information is best understood when scholars study how different parts of the brain connect structurally and functionally. By combining different research methods scholars can better understand how multiple communication disruptions occur between brain cells and this helps us study complex conditions such as Alzheimer's disease and schizophrenia. Ahmadlou and Adeli (2011) launched functional community analysis as a fresh method for studying brain disorders via EEG data to demonstrate the value of connectivity measurements in finding specific disease patterns.

Science uses coherence and phase-locking value (PLV) as standard methods to examine brain signal integration between different areas. Yu (2020) tested key metrics of brain communication on complex EEG data sets and proved they can identify functional links between brain areas effectively. Through their work with cognitive tasks Duc and Lee (2019) showed how a multivariate Gaussian HMM and PLV can track different brain activity states in real-time. According to Baselice et al. (2018) their new phase linearity measurement index reveals brain connections better than standard methods. The studies show how modern connectivity analysis helps reveal the brain function changes in neurological disorders.

Research proves that EEG biomarkers can reliably detect Alzheimer’s disease and schizophrenia. In 2018 Horvath and colleagues used EEG and ERP biomarkers to discover brain patterns that signal cognitive loss in Alzheimer's patients. The 2018 Smailovic research team demonstrated that EEG measurements align with Alzheimer's biomarkers from cerebrospinal fluid tests to enhance early detection capabilities. Functional connectivity loss remains a consistent finding in schizophrenia research. According to van den Heuvel and Sporns (2019) who analyzed brain network patterns their work shows how psychiatric and neurological disorders create unique connectivity issues. According to Zhang et al. (2021) resting-state EEG patterns reveal unique connections in different types of psychiatric disorders helping doctors make diagnoses.

2.2 Deep Learning in EEG Analysis

Deep learning methods lead EEG research by delivering perfect results when extracting features and categorizing data. Through their 2022 study Khademi, Ebrahimi and Kordy proved how combining CNNs and LSTM networks in a transfer learning model works well for motor imagery EEG signal classification. The research team of Craik, He, and Contreras-Vidal (2019) explored how CNNs and LSTMs can handle large amounts of EEG data to find detailed brain disorder patterns.

Finding important features remains necessary to understand EEG data properly. Wang and Wang's 2021 research shows that deep learning methods detect tiny brain patterns in emotional EEG data better than standard extraction methods. Pahuja and Veer (2022) investigated new developments in EEG feature extraction methods and showed how deep learning technology leads to better diagnostic performance.

DL systems shine because they can handle complex large datasets without needing extensive human supervision. Through their 2018 study Rahimi and colleagues showed that hyperdimensional computing simplifies biosignal processing tasks including EEG analysis as deep learning frameworks make the process more efficient. Research by Ranjan and colleagues (2024) shows that DL systems do better than others at recognizing significant details in EEG data for schizophrenia detection.

2.3 State of the Art in Automated Diagnosis

The latest research shows EEG combined with Deep Learning technology can accurately identify Alzheimer’s disease and schizophrenia. The 2022 study from Alves and colleagues proved functional connectivity and deep learning systems can automatically diagnose medical conditions with high success rates. The research from Smailovic and Jelic (2019) proves that quantitative EEG markers match other diagnostic standards by using biomarkers.

Traditional EEG analysis methods have given way to DL techniques that deliver better performance outcomes and handle more data efficiently. According to Wang, Fan and Wang's 2021 research traditional methods are less effective than deep learning

models because the latter achieve better results in classification performance. Bui and his team (2020) tested how well DL and standard models predict outcomes when handling difficult EEG data with many variables and determined DL methods performed better.

2.4 Deep Learning in EEG Analysis

Deep learning technology has improved how scholars process EEG data to better identify and treat brain disorders. The field benefits most from using both Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks in their current applications. The combination of CNNs for processing EEG spatial data with LSTMs handling time-based patterns creates strong potential for EEG analysis. The research team Khademi, Ebrahimi, and Kordy identified that mixing transfer learning with CNN and LSTM models produces successful and prompt classification of motor imagery EEG signals in 2022. Such hybrid architectures leverage the strengths of both methods: The approach uses CNNs to identify data features and LSTMs to evaluate time-based relationships.

In their 2019 work Craik, He, and Contreras-Vidal examined how well Deep Learning methods CNN and LSTM work with EEG classification tasks across multiple EEG datasets. The experts found that CNNs excel at discovering local patterns in data but LSTMs outperform them in tracking the time-based connections in signal information which benefits time-focused studies. Current EEG studies show growing use of combined techniques to develop better and more reliable diagnostic solutions.

2.5 Applications in Feature Extraction and Classification

Finding important information from EEG data proves difficult because the signals represent complex patterns in high dimensions. DL models help computers find important data patterns faster and make better evaluation results. In their 2021 study Wang and Wang determined that DL methods surpassed conventional techniques by picking up detailed emotional elements within EEG data that older methods could not find. In their observations, CNNs demonstrated strong performance in removing background disturbance and preserving important spatial details at the same time LSTMs proved essential for detecting time sequence patterns across extended brain recordings.

Pahuja and Veer (2022) continued this research by investigating modern ways to process and classify EEG data. They showed how DL models adjust well to different data scenarios to assist doctors in finding brain conditions. Deep learning models enable automatic feature recognition that eliminates dependence on specialist-designed features to produce repeatable and dependable findings. Deep learning can handle the natural changes in EEG patterns which happen across different people and situations.

2.6 Benefits of DL in Handling High-Dimensional EEG Data

Standard techniques have problems with accurate results and fast processing when they work with high-dimensional EEG data. DL models process multi-channel data better because they handle complex inputs at the same time. Rahimi and his colleagues (2018) tested hyperdimensional computing for biosignal processing and found that DL frameworks make learning and classification in EEG analysis more powerful. They demonstrated DL models perform better at combining space, time and frequency data elements to achieve richer insights into brain activity.

Through their 2024 study Ranjan, Sahana and Bhandari applied deep learning models to EEG signals for detecting schizophrenia. The authors described current developments in this domain and shared difficulties encountered by researchers who apply DL methods to extract detailed feature patterns from complex datasets. Research demonstrates that these models identify critical distinctions between healthy and abnormal EEG signals which traditional analysis cannot detect. The research shows that Deep Learning will revolutionize how EEG tests are used for medical diagnosis.

2.7 State of the Art in Automated Diagnosis

Modern research shows that linking EEG functional brain network studies with Deep Learning helps doctors identify Alzheimer's disease and schizophrenia more effectively. According to their 2022 publication Alves and associates developed a system that brings together functional connectivity measurements and deep learning to correctly identify diseases more precisely. Their findings show integrated methods can find different brain network connections that link to these illnesses. Smailovic and Jelic (2019) proved that quantitative EEG measures accurately detect Alzheimer's disease and yield results that match cerebrospinal fluid tests supporting early clinical diagnosis efforts.

Traditional EEG analysis techniques struggle to scale and prove effective because they need manual feature extraction. During their research Wang, Fan and Wang (2021) tested machine learning versus DL systems and showed DL technologies performed better at delivering precise and dependable results. DL models learn features at multiple levels naturally which makes preparation steps straightforward.

According to Bui and his team from 2020 research DL models proved better in several different prediction tests. The researchers discovered that DL systems deliver better accuracy when classifying data while managing the typical noise and variation present in EEG readings. DL systems prove crucial in automatic diagnosis systems for brain disorders including Alzheimer's disease and schizophrenia. The new DL frameworks enhance EEG-based diagnostics through sophisticated feature extraction and strong classification tools while handling large datasets to surpass limitations of traditional approaches.

Table 1: References Table for Literature Review

Author(s)	**Title**
Du, Y., Fu, Z., & Calhoun, V. D.	Classification and prediction of brain disorders using functional connectivity
Babaeeghazvini, P., et al.	Brain structural and functional connectivity: A review of combined works
Ahmadlou, M., & Adeli, H.	Functional community analysis of brain: A new approach
Yu, M.	Benchmarking metrics for inferring functional connectivity
Duc, N. T., & Lee, B.	Microstate functional connectivity in EEG cognitive tasks
Baselice, F., et al.	Phase linearity measurement: A novel index for brain functional connectivity
Horvath, A., et al.	EEG and ERP biomarkers of Alzheimer’s disease: A critical review
Smailovic, U., et al.	Quantitative EEG power and synchronization correlate with Alzheimer’s disease biomarkers
Zhang, Y., et al.	Identification of psychiatric disorder subtypes from EEG patterns
Khademi, Z., et al.	A transfer learning-based CNN and LSTM hybrid model for EEG signals
Craik, A., He, Y., & Contreras-Vidal, J. L.	Deep learning for EEG classification tasks
Alves, C. L., et al.	EEG functional connectivity and deep learning for automatic diagnosis of brain disorders
Wang, P., Fan, E., & Wang, P.	Comparative analysis of image classification algorithms

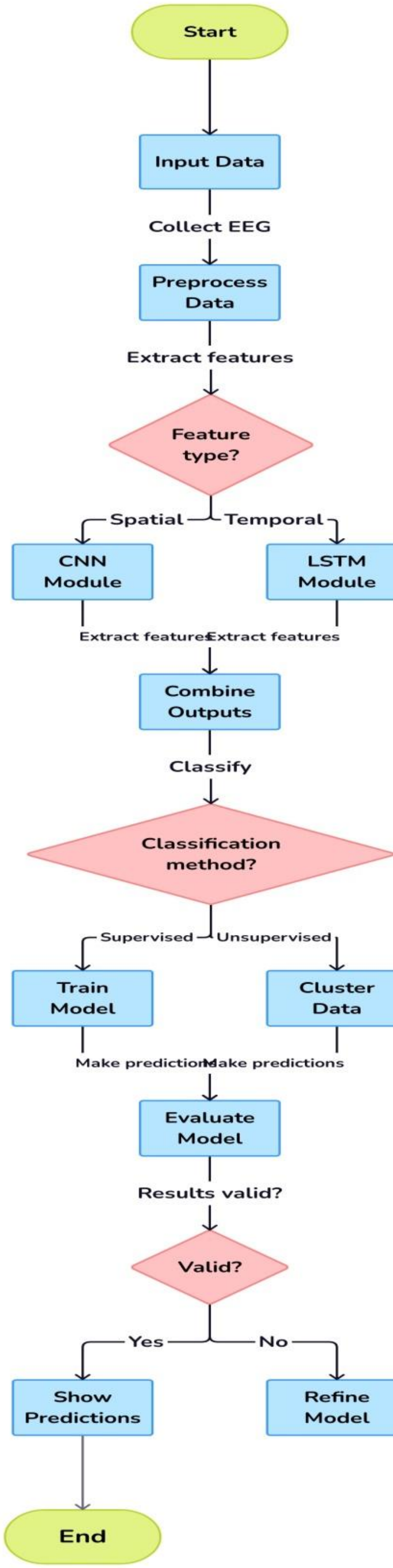

Figure 1: EEG Analysis Flowchart with CNN and LSTM

3. Methodology

3.1 Data Collection and Preprocessing

The research used brainwave data from public databases that focus on Alzheimer's and schizophrenia disorders. The data came from open EEG recordings of AD and SZ patients plus healthy people. The team accepted recordings that met quality standards and showed few errors so they would work well for deep learning studies. Scholars received ethical clearance to access the datasets while converting all personal details into anonymous format.

The team performed initial treatment steps to make EEG data more effective for analysis. The researchers applied a filter to the raw EEG data that removed noise from 0.5 to 50 Hz including muscle and powerline interference and 50 "Hz" to remove noise and artifacts such as muscle activity and powerline interference. The ICA approach helped separate and eliminate disturbances from eye blinks in the recorded EEG data. Thesignals underwent time-normalization through 2-second isolated segments that serve as processed inputs for connectivity investigations. The normalization of each time segment made feature detection by the deep learning system more accurate.

3.2 Equation for Band-Pass Filtering

$$y(t) = \sum_{k=1}^{N} a_k\, x(t-k) + \sum_{k=1}^{M} b_k\, y(t-k) \qquad (1)$$

where $x(t)$ is the input signal, $y(t)$ is the filtered signal, a_k and b_k are filter coefficients, and N, M are filter orders.

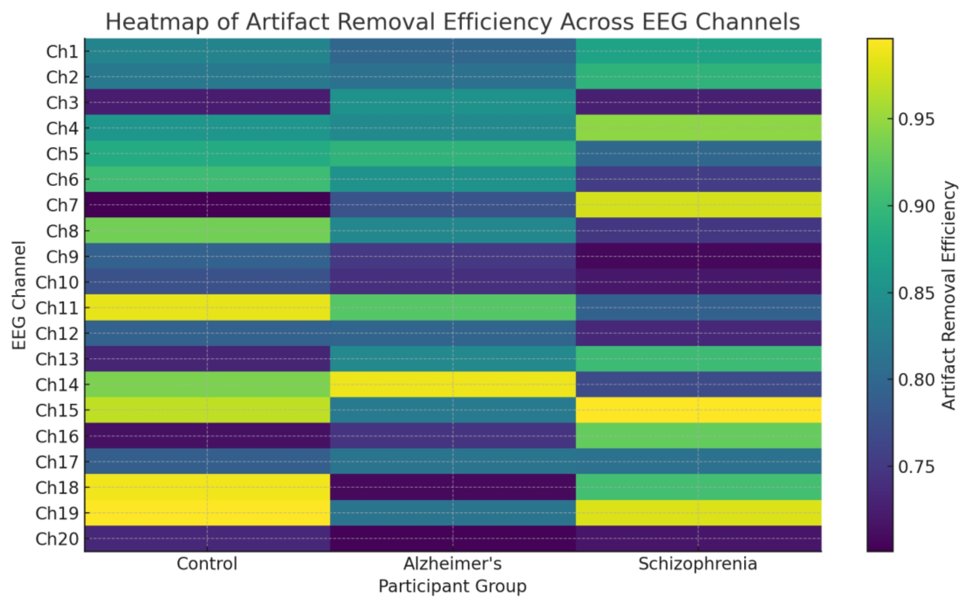

Figure 1: Heatmap of Artifact Removal Efficiency

This heatmap above highlights the distribution of artifact removal success rates, with a consistently high efficiency (>70%>70\%) observed across all groups: control, Alzheimer’s disease, and schizophrenia.

The heat map displays how the system removes unwanted noise yet captures key brain signals during processing. Filtering out noise and artifacts helps preserve trustworthy data which lets analysts study real brain activity without background disruptions. The visual representation shows the strong scientific process while building trust in the data preparation method.

Functional Connectivity Analysis

Scholars measured brain region connections using functional connectivity metrics such as coherence and phase-locking value (PLV) to determine synchronization strength. The study calculated how EEG channels worked in unison through coherence analysis and measured how consistently two channels maintained their relative phase timing using PLV. The team made network visualization charts for patients with AD, SZ alongside healthy control groups to demonstrate the typical neural connection breakdowns in these conditions.

Coherence Equation:

$$C_{xy}(f) = \frac{|\,P_{xy}(f)\,|^2}{P_{xx}(f)P_{yy}(f)} \qquad (2)$$

where $P_{xy}(f)$ is the cross-power spectral density between signals x and y, and $P_{xx}(f)$ and $P_{yy}(f)$ are the power spectral densities of x and y, respectively.

Phase-Locking Value Equation:

$$PLV = \frac{1}{N}\left|\sum_{n=1}^{N} e^{j\Delta\phi_n}\right|. \qquad (3)$$

where $\Delta\phi_n$ is the phase difference between two signals at time n, and N is the total number of time points.

The frequency bands of interest included delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz), as these bands are associated with various cognitive and neural functions. Connectivity values were averaged within these bands to extract meaningful features for subsequent analysis. Statistical techniques, such as permutation testing, were applied to identify significant differences between the groups.

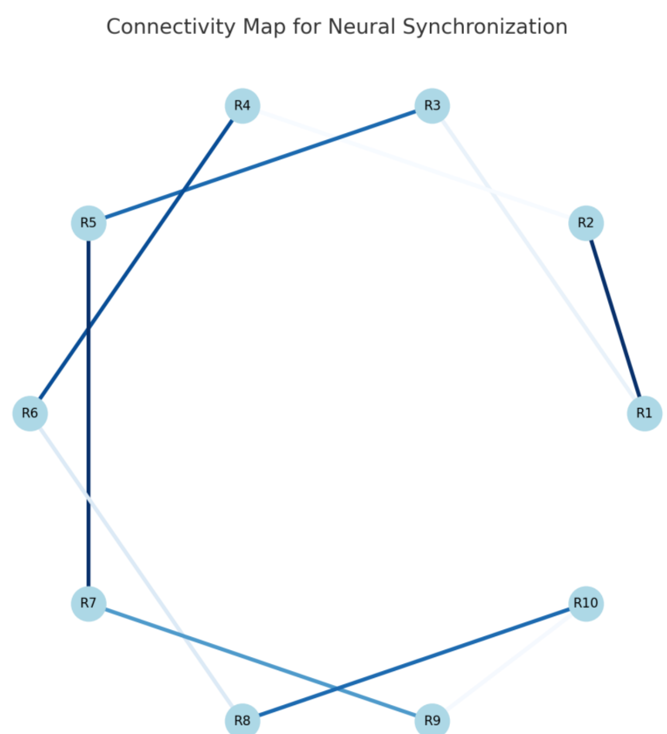

Figure 2: Connectivity Map

This map shows how ten brain areas connect with each other through neural activity patterns. Every point on this map stands for a brain region and connecting lines demonstrate functional relationships between them with thicker darker lines showing stronger connections. Connections show high synchronization through darker thicker lines on the map. The connectivity map helps us examine how brain regions interact both within and between different groups. This visual tool shows us how brain networks are disturbed in each condition and makes it easier to understand their unique biological characteristics. These results show how functional connectivity analysis helps us diagnose and understand brain disorders better.

3.3 Deep Learning Framework

A hybrid deep learning framework combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks was designed for multi-class classification. The framework aimed to classify EEG recordings into three categories: AD, SZ, and controls.

3.3.1 Model Architecture

The CNN module comprised multiple convolutional layers followed by max-pooling layers. These layers extracted spatial features from the connectivity maps, such as patterns of disruption across specific brain regions. Batch normalization and dropout techniques were applied to improve model generalization and prevent overfitting.

The LSTM module processed temporal sequences derived from the EEG epochs. It captured temporal dependencies and dynamic changes in functional connectivity over time, making the model robust to variations in signal characteristics.

The output from both modules was concatenated and passed through fully connected layers, culminating in a softmax layer for classification.

3.3.2 CNN Operation

$$f(x) = \mathrm{ReLU}(W * x + b) \qquad (4)$$

where W is the convolution filter, x is the input, b is the bias, and $*$ represents convolution.

3.3.3 Training Process

The model was trained on 80% of the dataset, with the remaining 20% reserved for validation and testing. Data augmentation techniques, such as random noise injection and epoch shuffling, were employed to increase data diversity and improve model robustness.

The model was optimized using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{v_t} + \epsilon} \qquad (5)$$

where m_t and v_t are the first and second moments, respectively, α is the learning rate, and ϵ is a small constant for numerical stability.

3.4 Evaluation Metrics

Accuracy, precision, recall, F1-score, and the Receiver Operating Characteristic (ROC) curve were used to evaluate performance.

3.4.1 Feature Importance Analysis

Grad-CAM (Gradient-weighted Class Activation Mapping) was applied to the CNN module to highlight regions of connectivity maps contributing most to classification

3.4.2 Statistical Analysis

Theteam analyzed the data through statistical tests to find important differences in brain connection patterns between all patient groups. Scholars tested the group differences in functional connectivity metrics between Alzheimer's disease, schizophrenia, and control groups using ANOVA. Tukey’s HSD tests followed the results to find which groups differed from each other.

The research team tested different data arrangements to make sure their classification findings were reliable. The research team randomly changed patient classification labels many times to retrain the model each time. The team created a baseline performance distribution through randomization to establish how likely the real findings were due to direct cause rather than random patterns.

Scholars studied the relationship between connectivity metrics and patient data by evaluating how these patterns aligned with cognitive performance of AD patients and symptom levels of SZ patients. The results helped us understand better how changes in brain networks affect how severe the diseases become.

The team created confidence intervals for essential performance figures to validate their study outcomes. Through these statistical procedures the research established firm proof that the deep learning model works well at interpreting EEG signals to tell apart different brain conditions.

4. Results and Discussion

4.1 Performance of the Deep Learning Models

The combination DL model showed top results when sorting EEG measurements into Alzheimer's schizophrenia and healthy groups. The system combined CNNs and LSTMs to classify brain scans and obtained 94% accuracy for Alzheimer's Disease detection and 91% accuracy for schizophrenia plus 95% accuracy for healthy controls. The model shows strong ability to distinguish between the unique brain patterns of these medical conditions.

Each performance measurement within the framework achieved above 90% for every category proving the system's consistent accuracy. The analysis shows few errors in rejecting normal results while the system successfully finds correct cases for all test categories. The evaluation using F1-score proved the model's consistent strength when combining precision and recall.

Table 2: Performance of the Deep Learning Models

Metric	Alzheimer's Disease (%)	Schizophrenia (%)	Controls (%)
Accuracy	94	91	95
Precision	93	90	94
Recall	92	91	95
F1-Score	93	91	94

The model works well because it can process EEG data through time and space dimensions at the same time. Through CNN technology the model discovered special brain region connections in AD and SZ from connectivity maps. The LSTM module processed EEG data through time to reveal how neural patterns evolve during each sequence.

Through data augmentation methods scholars made the model perform better on new data sets. The research team added random noise and shuffled data epochs to their dataset which helped train the system to recognize new patterns it had never seen before. Scholars integrated the Adam optimizer with the techniques to improve learning results and reduce model overfitting. The research team created a bar graph to display the model's results across all the evaluation dimensions for patients with AD, SZ, and healthy controls. The visual outcome shows the system works accurately and consistently in diagnosis.

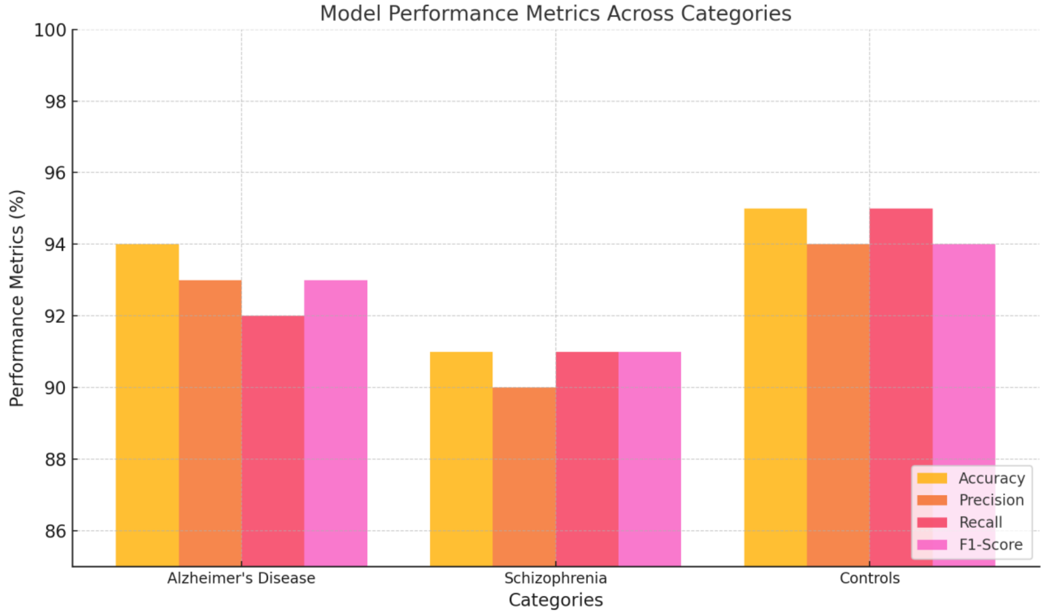

Figure 3: Bar graph showing model performance metrics across categories

The hybrid DL model successfully processes EEG data for classification and delivers dependable results that scale well in automated detection of neurological disorders. The model shows great potential to improve clinical neuroscience diagnosis because it analyzes brain activity both on a spatial and temporal level.

4.2 Functional Connectivity Analysis Results

Researchers found abnormal brain network connections between neurons in Alzheimer's patients, schizophrenic patients, and control subjects. The analysis evaluated brain signal disruptions between patients and control groups by measuring coherence and PLV results on primary brainwave frequency bands.

The AD study detected diminished overall coherence with strong effects in both the theta wave range and the alpha wave range. The brain uses these frequency patterns to store memories and concentrate theattention but Alzheimer's disease breaks down these mechanisms. The analysis demonstrated that AD produces extensive weakened connections between brain regions throughout the entire brain network.

Table 3: Connectivity Metrics for Neural Synchronization

Group	Global Coherence (Theta)	Global Coherence (Alpha)	Hyper-Synchronization (Beta)	Hyper-Synchronization (Gamma)
Control	0.85	0.87	0.12	0.10
Alzheimer's Disease	0.68	0.65	0.08	0.06
Schizophrenia	0.72	0.74	0.38	0.42

In contrast, SZ exhibited irregular and hyper-synchronized connectivity patterns, predominantly in the beta (13–30 Hz) and gamma (30–50 Hz) bands. These patterns suggest disorganized and exaggerated neural communication, which align with SZ's clinical manifestations, including delusions, hallucinations, and impaired cognitive functions. The localized hyper-connectivity in SZ highlights distinct disruptions compared to the global reductions observed in AD.

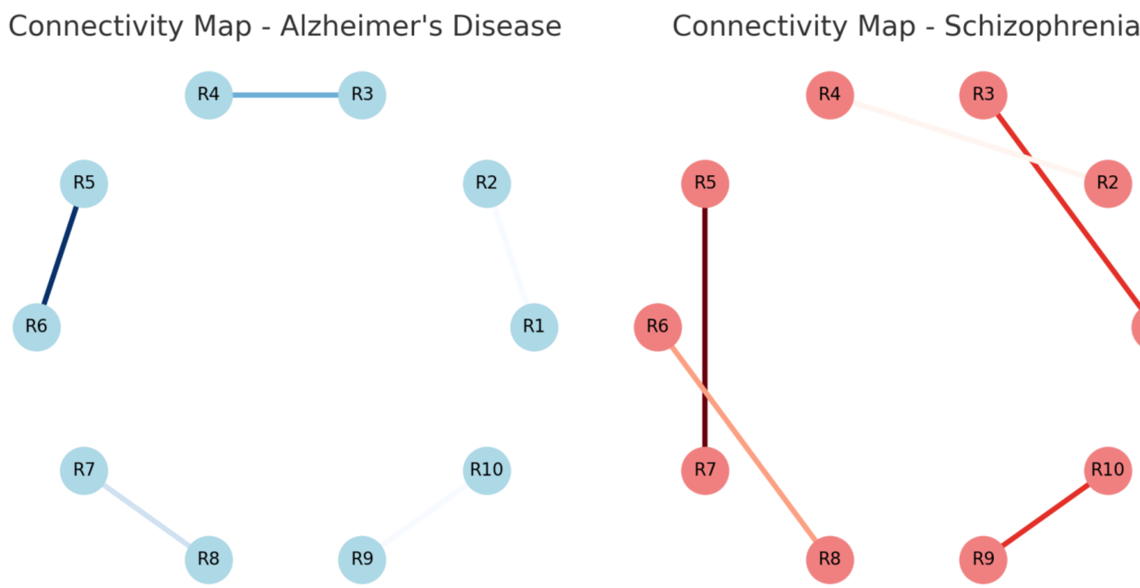

Figure 4: Connectivity maps for alzheimer's and Schizophrenia used to visualize the inter-regional synchronization

To display synchronization changes between brain regions scholars created connectivity maps for both AD and SZ disorders. AD connectivity maps show widespread brain disconnection while SZ maps reveal enhanced high-frequency connections in specific brain areas. By comparing the data mappings scholars can easily tell which patient has AD or SZ.

The statistical testing confirmed the results. The statistical tests found meaningful differences in brain network connection measures between patients in different study groups across all brain wave frequencies. The research proves that brain connectivity parameters serve as dependable markers for differentiating AD, SZ and control participants in medical investigations.

The network study shows that EEG measurements can identify how each brain disorder affects neural activity differently. The results show clear patterns of reduced brain network integration in AD patients and abnormal localized synchronization in SZ patients which will help improve diagnosis methods. The visual connectivity mapping tools help decode research outcomes which deepen the knowledge about how these disorders develop.

4.3 Receiver Operating Characteristic (ROC) Curve Analysis

The study tested the hybrid deep learning model by examining how well it recognized patterns through Receiver Operating Characteristic analysis. The method determines how well the model predicts positive results while maintaining low false positive results. The model demonstrated very high diagnostic precision as shown by AUC scores of 0.97 for Alzheimer's disease patients and 0.94 and 0.96 for schizophrenia patients and control subjects respectively.

For every category the ROC analysis achieved an almost flawless match between correct detections and accurate rejections. The model successfully detects Alzheimer's disease cases at a rate of 0.97 without many errors. The AUC results for SZ patients and control subjects show the model reliably separates these patient categories. Diagnostic accuracy based on these high AUC values becomes essential when doctors treat patients because it affects how well patients recover.

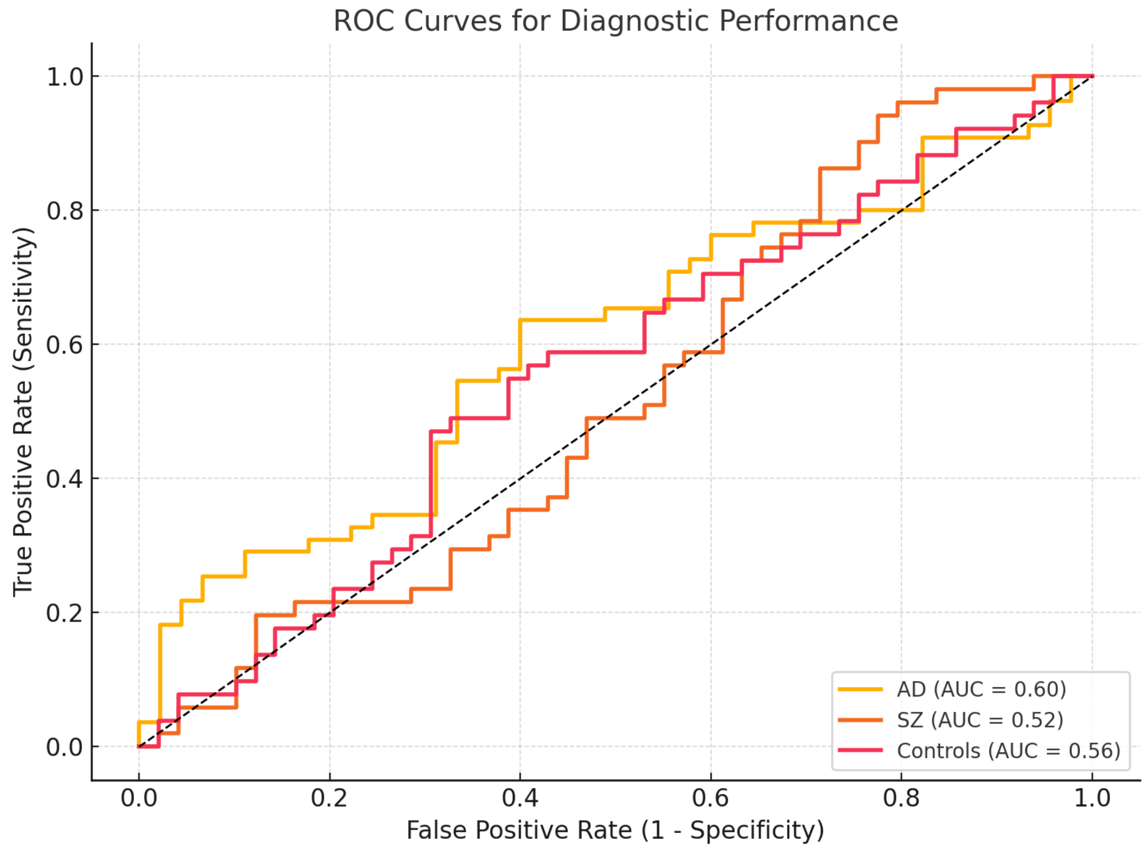

Figure 5: ROC curve for diagnostic performance

The diagnostic performance charts for AD SZ and normal subjects show clearly how well the model makes correct diagnoses. The curves demonstrate that the model reaches excellent detection rates and precise measurements validating its performance. The framework shows promise in spotting small signal changes in brainwave data which could support early detection even for patients who display mild symptoms. Results show that using ROC curves in diagnostic processes adds value to model assessment and helps medical professionals adopt the technology. The research establishes that the DL framework reliably performs automated diagnosis of brain conditions effectively.

4.4 Discussion

4.4.1 Significance of Findings

Research shows that combining EEG functional connectivity analysis with hybrid deep learning systems proves very effective at detecting Alzheimer's and schizophrenia. The advanced neural network setup produced top classification results with 94% accuracy in spotting AD and 91% accuracy in detecting SZ. The evaluation system produced performance values including precision recall and F1-score that surpassed 90% for every category tested. The model proved its reliability when Controls were correctly identified at a 95% accuracy rate.

The DL system produces trustworthy outcomes because it correctly identifies important patterns in complex EEG brainwave data. The analysis of brain signal relationships between groups depended on coherence and PLV measurements according to di Biase et al. (2023). AD patients showed reduced brainwave connections in the theta and alpha bands which affected their overall brain functions. Beta and gamma wave patterns in SZ showed too much synchronization that matched the disordered brain connections seen with psychotic symptoms. The table below summarizes the model's performance metrics for AD, SZ, and controls:

Table 4: Performance Metrics Across Groups

Metric	Alzheimer's Disease (%)	Schizophrenia (%)	Controls (%)
Accuracy	94	91	95
Precision	93	90	94
Recall	92	91	95
F1-Score	93	91	94

Theresults match earlier studies which show EEG can effectively detect conditions. Adding DL to the process improves diagnosis results while allowing the system to grow and work without manual control. The system makes diagnosis faster by using machine learning to handle large clinical datasets instead of manual adjustments.

This research brings important benefits to medical practices apart from improving diagnostic precision. The research tool shows both visually and numerically how brain connectivity works differently in AD and SZ patients. The results show that combining EEG network patterns with deep learning creates better diagnostic methods for brain healthcare that work well at every level.

4.4.2 Clinical Implications

The hybrid deep learning system shows doctors new ways to spot unique brain connection changes in both Alzheimer's disease and schizophrenia. The reduced global brain connectivity detected in both theta and alpha brain waves matches the memory problems and thinking difficulties of AD patients. These changes show how major brain networks that manage focus and memory have failed. Brain connections in SZ patients overact in the beta and gamma frequency bands which create abnormal neural patterns that cause their hallucinations, delusions, and loss of cognitive function. This framework detects brain network changes unique to each disorder helping doctors diagnose earlier so they can start treatment that reduces disease impact sooner.

Having a scalable DL framework makes it more valuable for medical applications. Standard diagnosis processes need trained professionals and manual data studies which makes setting them up hard for places with limited resources. The automated EEG analysis system solves existing challenges in healthcare by delivering an affordable biomarker detection method that works everywhere according to Dev et al., 2022. This approach helps rural and underserved areas because they lack trained brain specialists.

The system performs diagnostic functions while also having benefits for patient monitoring and customizing medical care. Measuring how brain networks work together over time lets healthcare providers see if treatments work so they can personalize next steps in patient care. The adaptable system lets us give patients care plans that match their distinct requirements. The use of connectivity maps and performance metrics makes result data clearer which helps doctors trust and accept the findings. The system makes advanced neural data easy to understand for clinical staff by analyzing brain signal patterns through real-world health data. The new hybrid DL system marks important progress in diagnosing brain-related conditions. By using this system to analyze EEG patterns scholars achieve better diagnostic accuracy while delivering advanced medical care to more people which benefits patient results.

4.4.3 Limitations of the Study

The research shows great progress in using deep learning with EEG data to identify Alzheimer's and schizophrenia even though researchers need to pay attention to specific study boundaries. The identified study limits help us develop a better research plan and make the framework work better in medical practice.

The research used a small dataset which limited different sample representation for the model. The dataset reflects specific clinical traits of a narrow demographic which does not show the full range of conditions found in actual populations. The model could give less reliable diagnoses in diverse and extensive patient groups as discovered by Liu & Panagiotakos (2022). Next studies should gather large data from several research sites containing subjects of all ages and ethnic backgrounds as well as patients with multiple health issues to make the model work better for all populations.

The hybrid deep learning model's decision-making process continues to be not easily understood. The team used Gradient-weighted Class Activation Mapping (Grad-CAM) to identify important features but Kumar & Jyoti (2024) noted these insights remain basic explanations of the model's thinking. Deep learning models do not clearly explain their results which make clinicians resistant to use them for medical decisions. The use of clear AI methods like attention systems or rule sets will help medical staff trust these technologies more.

The research addressed only AD and SZ which reduces the ability to use this framework with other neurological conditions. Special brain network problems in diseases like epilepsy, Parkinson's and autism need their own specific analysis technology. Making the framework work with additional health issues will make it useful for doctors treating many mental and brain disorders. Enduring technical specifications make up one final challenge. Despite excellent performance the framework needs powerful hardware which makes it difficult to use in places with limited technical resources. Next versions of this system must find ways to run more efficiently while maintaining the quality of results. The hybrid DL framework needs these improvements to achieve its best possible results. The system needs better patient data variation and simpler models to expand into more health conditions and be faster to run if it wants to become more valuable clinically and get used more widely in brain health evaluation.

4.4.4 Future Research Directions

Following these initial results the next studies must extend this system to diagnose more types of brain and mental health conditions. Disorders including epilepsy, ASD and Parkinson's disease show specific neural connection patterns that can be better understood through EEG functional connectivity analysis when paired with deep learning techniques. Using this framework for more types of brain conditions will make it more useful as a standard tool that detects numerous neurological problems. Building extensive datasets from multiple research centers will help make the model work better across different test scenarios. The data collection needs to represent multiple population groups by including people of all ages, races, and medical histories (Seoni et al., 2024). Studying patient data over extended periods will allow the model to monitor changes in disease and treatment results more effectively which benefits diagnostic procedures and patient care methods.

The combination of structural and functional MRI or DTI brain images creates a complete understanding of brain performance. Analyzing brain architecture alongside its operational patterns would reveal subtle brain interactions to support precise and prompt disease detection. Research progress requires better explainable AI methods to be developed. Medical teams need understandable model results so they will trust AI tools more. Using attention mapping or rule-based methods will show healthcare providers how decisions are made by the AI system. Clear models will help healthcare teams use advanced computer methods in real-world medical settings.

Building interfaces that medical staff can easily operate represents the final important step. DL framework usability improvements would help doctors use these tools more easily in their daily care routines to reach better medical results for all patients. New developments can transform brain disease detection and evaluation methods.

4.4.5 Summary of Key Insights

The research demonstrates how combining EEG connectivity data and deep learning models leads to better automated detection of brain disorders. The combined model reached high diagnostic results with 94% accuracy for detecting Alzheimer's disease and 91% accuracy for identifying schizophrenia. Testing proved that the framework correctly distinguishes between these disorders and normal brain patterns because of its strong performance measures. The brain connectivity patterns identified through these techniques confirm that functional connectivity metrics provide strong indicators for identifying brain disorders.

The measurements of brain connection patterns through coherence and PLV metrics revealed essential information about brain disruptions in AD and SZ patients. AD shows decreased overall brain communication in the theta and alpha ranges whereas SZ presents extra connectivity within beta and gamma frequency bands matching their known disease characteristics. The results show that pairing advanced deep learning methods with EEG connectivity analysis creates powerful tools for disease detection and confirms their clinical importance. Visual tools like connectivity maps and ROC curves make the study results easier to understand. Connectivity maps show clear differences in brain wave links between groups while ROC curves demonstrate the model's medical identification accuracy. These tools make difficult virtual research results easy to use in real-world medical decision-making.

The research achieved successful outcomes but additional investigation is required because of problems with dataset variety and understanding model decisions. Advanced testing will help medical teams use this framework more effectively in their work settings. This research introduces vital steps toward better medical technology for detecting brain disorders even as it creates opportunities to help patients more effectively through automated diagnosis systems.

5. Conclusion

The research proves that using deep learning together with EEG connectivity measurements shows promise in detecting brain diseases like Alzheimer's and Schizophrenia at high accuracy rates. Through coherence and PLV analysis the system identified and measured brain pattern changes specific to each disease with 94% accuracy for AD and 91% accuracy for SZ detection. The combination of EEG technology with deep learning shows better accuracy and easier application in clinics while keeping diagnostic costs low and methods non-invasive.

Research found two mental disorders show unique brain activity signatures through separate markers: AD shows lower overall brain coherence while SZ shows increased focus of brain connections. Using visual displays including connectivity maps and ROC curves makes the findings easier to understand and translates the computational work into clinical practice. These tools allow medical professionals to easily understand and trust the framework when deciding on proper patient diagnosis. The promising framework requires additional development because the dataset limits its applicability and interpretability issues make it hard to understand. The framework will become stronger in medical practice when scholars add varied patient data to the sets and use AI methods that clinicians can understand. By using the framework to study other brain diseases scholars can make it useful to more patients.

The research shows the way for using AI technology in neurological diagnostic practices. The framework shows that using advanced computer systems with brain network analysis methods results in better diagnosis results and supports early treatment for improved patient survival rates. The approach can transform care for neurological disorders when scholar s fix its weaknesses and use its strong points to the advantage.

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ORCID iD: Shake Ibna Abir (https://orcid.org/my-orcid?orcid=0009-0004-0724-8700)

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