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Internet of Medical Things (IoMT)-Enabled Explainable Graph Learning System for EEG-Based Schizophrenia Diagnosis in Smart Healthcare Environments

Ali Saleem Khalaf Lababneh[1], Dr. Fuad S. Al-Duais[2], Aseel Smerat[3], and Dr. Rasha M. Abd El-Aziz[4*]

[1]Lecturer, Department of English Language & Literature, College of Science and Humanities Studies in Al-Kharj, Prince Sattam Bin Abdulaziz University, Al-Kharj, Saudi Arabia. a.lababneh@psau.edu.sa, https://orcid.org/0009-0009-8293-0159

[2]Associate Professor, Department of Mathematics, College of Science and Humanities in Al-Kharj, Prince Sattam Bin Abdulaziz University, Al-Kharj, Saudi Arabia. f.alduais@psau.edu.sa, https://orcid.org/0000-0002-2255-1167

[3]Lecturer, Department of Biosciences, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India; Lecturer, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan. smerat.2020@gmail.com, https://orcid.org/0009-0008-4600-509X

[4*]Associate Professor, Department of Computer Science, College of Computer and Information Sciences, Jouf University, Saudi Arabia; Associate Professor, Department of Computer Science, Faculty of Computers and Information, Assiut University, Assiut, Egypt. rmhassanien@ju.edu.sa, https://orcid.org/0000-0002-8975-6052

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Abstract

It is a mental illness with cognitive process disruption, self-monitoring impairment, and functional brain connectivity abnormalities. Electroencephalography is a non-invasive and high temporal resolution tool for brain activity analysis; however, the existing EEG-based diagnostic frameworks cannot account for the complex spatio-temporal relationship and interpretability for clinical decision making. This paper presents an Internet of Medical Things-enabled explainable graph learning approach, namely Neuro Graph Former-X, for automatic diagnosis of Schizophrenia within smart health care environments. In the proposed solution, wearable EEG sensors are used for real-time measurement of brain electrical activities, and communication protocols such as 5G and LoRaWAN are utilized for monitoring purposes. Pre-processing is carried out via bandpass filtering, Z-score normalization, and temporal segmentation to eliminate noise and decrease bandwidth. Next, Discrete Wavelet Transform is implemented to extract multi-resolution features, and Phase Locking Value is used to build dynamic functional brain connectivity graphs. Then, these graphs are fed into the hybrid deep learning model comprising Graph Attention Networks to learn the spatial features, Temporal Convolution Networks for temporal modeling, and Transformer encoders to extract global dependencies. In addition to this, the explainable AI module, which uses neurocognitive attention and Integrated Gradients, is introduced for improving the explainability of the model. As per

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*Corresponding author: Associate Professor, Department of Computer Science, College of Computer and Information Sciences, Jouf University, Saudi Arabia; Associate Professor, Department of Computer Science, Faculty of Computers and Information, Assiut University, Assiut, Egypt.

experimental results, it can be stated that the proposed model attains 96.84% Precision, 96.58% F1-Score, and 98.21% AUC, thereby performing better than existing machine learning and deep learning approaches. It has been proven from the results that the proposed approach is highly scalable and interpretable for schizophrenia diagnosis using IoT-enabled smart healthcare platforms.

Keywords: Internet of Medical Things (IoMT), Schizophrenia Diagnosis, EEG Signals, Graph Neural Networks, Explainable AI, Functional Connectivity, Smart Healthcare.

1 Introduction

Schizophrenia is one of the serious and complicated neuropsychiatric conditions defined by abnormalities in cognitive functions, perception, emotional control, and self-monitoring. The above problems have a considerable impact on the ability of an individual to differentiate between their thoughts and reality; hence, people experience hallucinations, delusions, and cognitive disorganization. Nowadays, Schizophrenia is considered to be not a dysfunction in some specific parts of the brain but rather a dysfunction in the functional interactions within various large-scale neuronal networks.

EEG has gained immense popularity as one of the major neuroimaging tools used for studying Schizophrenia because of its high temporal resolution, non-invasiveness, and capability to record real-time brain dynamics (Gholizadeh HamlAbadi et al., 2024). Nevertheless, EEG is inherently a non-linear, non-stationary process that is extremely sensitive to noise and artifacts. Consequently, conventional techniques cannot be applied to accurately measure complex interactions within the brain. Current EEG diagnostic models usually analyze signals independently, neglecting the dependence on space and interdependencies between regions of the brain.

In order to solve these problems, new research has focused on brain network modeling with functional connectivity and graph representations. According to this approach, EEG electrodes are considered as nodes, whereas the statistical or phase dependency between signals is presented through the edges of the brain graph model. Graph Neural Network (GNN) and other deep learning models have proved themselves efficient at identifying such dependencies. Nevertheless, most of these methods utilize static graph structures, which are unable to represent the dynamics of brain states, especially in diseases like Schizophrenia.

Another significant drawback of the existing AI-based diagnosis tools is their non-interpretable nature. Even though they have shown good performance in terms of classification accuracy, they are seen as black box models where clinicians cannot extract any information regarding why they predict something. In medicine, especially in mental disease diagnosis, interpretability is critical for clinical use. This means the necessity to develop explainable AI solutions that will be able to detect relevant brain areas and patterns responsible for the diagnosis.

Furthermore, current medical care systems are shifting to IoMT-based smart environments, where continuous monitoring of physiological data through wearable sensors and their transmission in real time via wireless communication networks becomes possible (Alshehri & Muhammad, 2020). The application of IoMT allows remote monitoring of health status, early disease detection, and constant patient assessment, which makes it very promising for mental health applications (Bin Heyat et al., 2025). Yet, the combination of IoMT with graph-based deep learning and explainable AI is still a complex scientific task.

In light of the above-mentioned problems, this research presents NeuroGraphFormer-X, an IoMT-enabled and explainable graph learning framework for diagnosing Schizophrenia from EEG data in the smart healthcare ecosystem (Al-Hajjar & Al-Qurabat, 2023; Misgar & Bhatia, 2024). In this system, a feature extraction approach based on wavelets along with PLV-based modeling of dynamic functional connectivity along with hybrid deep learning models consisting of GAT, TCN, and Transformer encoders is employed. Moreover, a neurocognitive attention mechanism and an Integrated Gradients explainability approach have been used to provide more insight into the problem.

Key Contributions

1. An IoMT-driven EEG monitoring system is introduced for the continuous diagnosis of Schizophrenia via wearable devices, edge computing, and secure smart healthcare communications.
2. The NeuroGraphFormer-X model is proposed, which combines GAT, TCN, and Transformer models, along with PLV-based dynamic brain graphs to detect EEG spatial-temporal correlations.
3. An explainable and secure AI solution is designed based on neuro-cognitive attention and the Integrated Gradients technique to attain 96.84% Precision and clinical insights into schizophrenia detection.

The structure of this paper is given as follows: Section I is about the introduction part of this paper, where the difficulties of the schizophrenia diagnostic process, brain connectivity estimation using the electroencephalography technique, and the necessity of IoMT-enabled explainable graph learning are introduced. Section II is about related works and provides a review of the IoMT-based healthcare system, EEG signal processing, graph neural network approaches, and explainable artificial intelligence techniques. It further identifies research gaps in these fields. Section III introduces the architecture of an IoMT-enabled smart healthcare system, including data collection from wearable devices, edge computing, communication platform, cloud computing services, and the NeuroGraphFormer-X method, which includes signal pre-processing, wavelet-based feature extraction, PLV-based graph construction, GAT-based spatial learning, TCN-based temporal learning, Transformer-based global dependency learning, and an explainability mechanism. Section IV presents the experiment configuration and comparative analysis with baselines to prove the effectiveness of our work. Section V interprets the results, which include the accuracy of the model and its interpretability. Furthermore, it proves that the IoMT-based approach is feasible.

2 Related Works

The combination of Internet of Medical Things (IoMT), artificial intelligence, and neuro-analysis by electroencephalography (EEG) has greatly helped improve the process of automated schizophrenia diagnosis within smart healthcare systems. The recent works focus on the evolution of EEG-based diagnostic algorithms to more intelligent, connected, and explainable methods that allow for real-time monitoring and decision-making. SzHNN is a hybrid convolutional neural network architecture designed by Sharma & Joshi, (2022) for schizophrenia identification using multichannel EEG data, which provides high classification accuracy due to deep feature extraction. But this method does not use any IoMT-based data stream and explainability.

In this regard, Li & Huang, (2023) proposed a reinforcement learning-based approach to feature selection for schizophrenia diagnosis in intelligent systems utilizing IoMT with smart healthcare, indicating that optimization of features in multidomain EEG is essential in IoT systems. In a similar vein, Ambeth Kumar et al., (2024) created an IoMT-based prediction model for mental disorders through EEG sensors and big data analytics, stressing the ability to monitor in real time. However, both studies prove that IoMT is necessary in providing constant brain monitoring, yet they lack graph-based modeling of brain connections.

Latest developments in the field of deep learning algorithms for diagnosing mental health disorders have shown better results but still lack transparency. The authors in Paraschiv et al., (2024) have designed a novel AI-powered electroencephalogram (EEG) monitoring system to detect Schizophrenia through connectivity-based learning. Another interesting approach has been provided by the authors in Singh et al., (2024) where they have presented a hybrid framework of graph convolutional networks and transformers for classifying mental disorders based on EEG signals.

Transformer and hybrid deep learning models have also been used in real-time healthcare settings. Dubey et al., (2025) presented TRANSHEALTH, which is a transformer model for identifying psychological distress in ambient healthcare settings and highlighted the significance of real-time learning. Likewise, Murugesan et al., (2025) talked about edge computing AI for biomedical applications and underlined the importance of distributed computing in healthcare analytics. All these findings justify the requirement for lightweight IoMT frameworks based on edge computing for real-time EEG data analysis.

A graph-based learning approach has shown its significance as an excellent paradigm for modeling brain connectivity. Zafeiropoulos et al., (2023) proved the efficacy of graph neural networks in monitoring neurological disorders like Parkinson's disease, indicating that the brain network is best modeled using graphs. Al-Qurabat et al., (2025) took the graph-based modeling approach one step further through the utilization of weighted visibility graphs and IoMT for epileptic seizure detection. This reinforces the need for adopting a graph-based model for diagnosing Schizophrenia from EEG signals.

Now, explainability and transparency in AI-powered health care systems have become an indispensable necessity for their implementation in clinical settings. According to recent surveys conducted by Singh & Sharma, (2024) and Ain et al., (2025), issues relating to interpreting AI for diagnosing mental disorders are discussed specifically in the context of using deep learning algorithms for analysis of EEG signals. The importance of multimodal fusion and interpretability of machine learning is further discussed by Hasib et al., (2023) and Alwakeel et al., (2023) in the context of smart cities' health care ecosystems.

Federated learning and distributed intelligence have also been investigated for improving the privacy and scalability in healthcare systems. In this context, Vajrobol et al., (2025) offered a complete study on the application of federated learning in mental healthcare, while Zeydan et al., (2024) discussed the distributed machine learning lifecycle management in cloud-based healthcare systems.

Moreover, sensor-based health care systems and wearable sensors have great significance in the implementation of continuous monitoring. The efficiency of wearable sensor technologies for smart living and neurological monitoring has been proven by Leelaarporn et al., (2021) and Khondakar & Kaushik, (2022). Moreover, Islam et al., (2025) stressed the significance of IoT-based wearable sensors in remote monitoring systems for healthcare.

Fourthly, current systematic and scientometric studies have validated that signal processing and AI-based diagnosis of mental health issues have undergone rapid developments in recent times. The research conducted by Prasasti et al., (2025) and Sadruddin et al., (2024) addresses various limitations in multimodal signal processing and mental stress identification using machine intelligence. It is therefore evident that despite the substantial advancement achieved in the diagnosis of Schizophrenia using EEG, it is imperative to develop an approach integrating IoMT-supported real-time sensing and brain connectivity models using graphs and explainable AI.

From the literature review, it can be seen that the current techniques either emphasize accuracy-oriented EEG classification using deep learning or use IoMT-driven monitoring techniques, but seldom combine both with graph representation of brain connectivity along with explainable AI. In addition to this, most of the current techniques lack real-time adaptability and clinical interpretability. Hence, there is considerable scope for research in designing an IoMT-driven explainable graph learning model that can effectively deal with brain connectivity dynamics and smart healthcare implementation in real time.

Table 1: Summary of related works

Ref	Methodology	Key Technique	Accuracy	Advantages	Disadvantages
(Misgar & Bhatia, 2024)	IoMT actigraphy-based ADHD diagnosis	Dimensionality reduction + ML	High (~90%+)	Efficient feature reduction, wearable-based monitoring	Limited EEG/brain connectivity modeling
(Singh & Sharma, 2024)	Systematic review of mental disorder detection	ML + physiological signal analysis	Not applicable	Comprehensive overview of methods and trends	No novel model, review-only
(Hasib et al., 2023)	Depression detection from social networks	ML & Deep Learning text analysis	Moderate–High (~85–90%)	Effective social media-based mental health prediction	Not EEG-based, lacks physiological grounding
(Islam et al., 2025)	IoT wearable healthcare systems	IoT + remote monitoring framework	Not reported	Enables continuous monitoring and telehealth	No deep learning or graph modeling
(Murugesan et al., 2025)	AI integration in biomedical systems	Edge AI + intelligent healthcare systems	Not reported	Strong scalability and real-time edge processing	Limited focus on schizophrenia/EEG graphs
(Zeydan et al., 2024)	Cloud-based distributed ML lifecycle	Cloud ML management frameworks	Not reported	Efficient distributed learning for healthcare data	No direct EEG or IoMT graph learning model
(Ain et al., 2025)	AI-based ADHD diagnosis trends	ML + healthcare analytics review	Not applicable	Identifies challenges and future directions	No experimental EEG model
(Khondakar & Kaushik, 2022)	Wearable sensing for long COVID	Biosensor-based physiological monitoring	Moderate (~80–85%)	Real-time wearable health monitoring	Limited neurological/graph learning analysis
(Gholizadeh HamlAbadi et al., 2024)	BCI in metaverse applications	Brain–computer interface + neural decoding	Not specified	Advanced brain signal interpretation	Not focused on schizophrenia diagnosis
(Leelaarporn et al., 2021)	Sensor-driven smart living systems	IoT sensor fusion frameworks	Not specified	Supports smart healthcare environments	No deep learning or EEG graph modeling
(Sadruddin et al., 2024)	Multimodal mental stress detection	ML + multimodal data fusion	Moderate–High (~85–92%)	Handles multimodal physiological signals	High complexity, limited explainability

Summary of table 1 presents the main features of contemporary research on the healthcare system based on IoMT, wearable sensing, multimodal analysis of physiological signals, and an AI-driven approach to the identification of mental disorders. It provides information about the method used, the main technologies, the accuracy achieved, if any, and the strengths and limitations of each study. Generally speaking, almost all approaches show significant potential in using IoT and machine learning to detect mental disorders, but they do not use EEG-based graph learning, IoMT streaming, and XAI principles. It once again shows how necessary it is to develop a unified model incorporating IoMT, dynamic modeling of brain connectivity, and graph learning.

3 IoMT-Enabled Smart Healthcare Information System Architecture

This system is to be implemented as an IoMT-powered smart healthcare information system that will transform raw EEG signal data into usable health information services. The system structure consists of wearable devices for EEG data acquisition, IoMT communication networks, edge and cloud computing systems, and explainable graph-based learning models. In total, the system can be divided into four main players: (i) the data acquisition layer; (ii) the communication and edge computing layer; (iii) the intelligent analytics layer; and (iv) the healthcare information service layer.

3.1 IoMT-Enabled Smart Healthcare Architecture

The suggested system is built as a smart healthcare system that uses the Internet of Medical Things (IoMT) to enable continuous diagnosis of Schizophrenia using EEG. In the design of the architecture, wearable multi-channel EEG devices are used to obtain brain signals from the subjects in a real-time environment and use IoMT communication protocols such as 5G and LoRaWAN to transmit them. The transmitted signals are processed at the edge gateway, and then the processed data is passed through a cloud-intelligent analysis module. At the analysis module, the graph learning model (NeuroGraphFormer-X) is used for the classification of Schizophrenia. The diagnosis output is finally made available to the clinicians via a healthcare dashboard.

Figure 1 shows the suggested IoMT-assisted explainable graph learning system for schizophrenia diagnosis from EEG data in a smart healthcare environment. This system consists of four interconnected layers, namely, (i) the IoMT-based data acquisition layer, where EEG data from multiple channels are acquired with the help of neuro-sensor devices; (ii) the communication and edge layer, where the signals are sent via secured IoT protocols and processed through lightweight procedures such as bandpass filtering, normalization, and segmentation; (iii) the intelligent analytics layer, which involves wavelet decomposition, PLV-based functional connectivity, and brain graph generation, after which hybrid deep graph learning via GAT, TCN, and Transformer models is conducted; and (iv) the healthcare service layer, where the final schizophrenia classification, visualization dashboard, and doctor decision making take place. Moreover, the proposed IoMT system incorporates the concept of a neuro-cognitive attention mechanism and an explainability approach using Integrated Gradients.

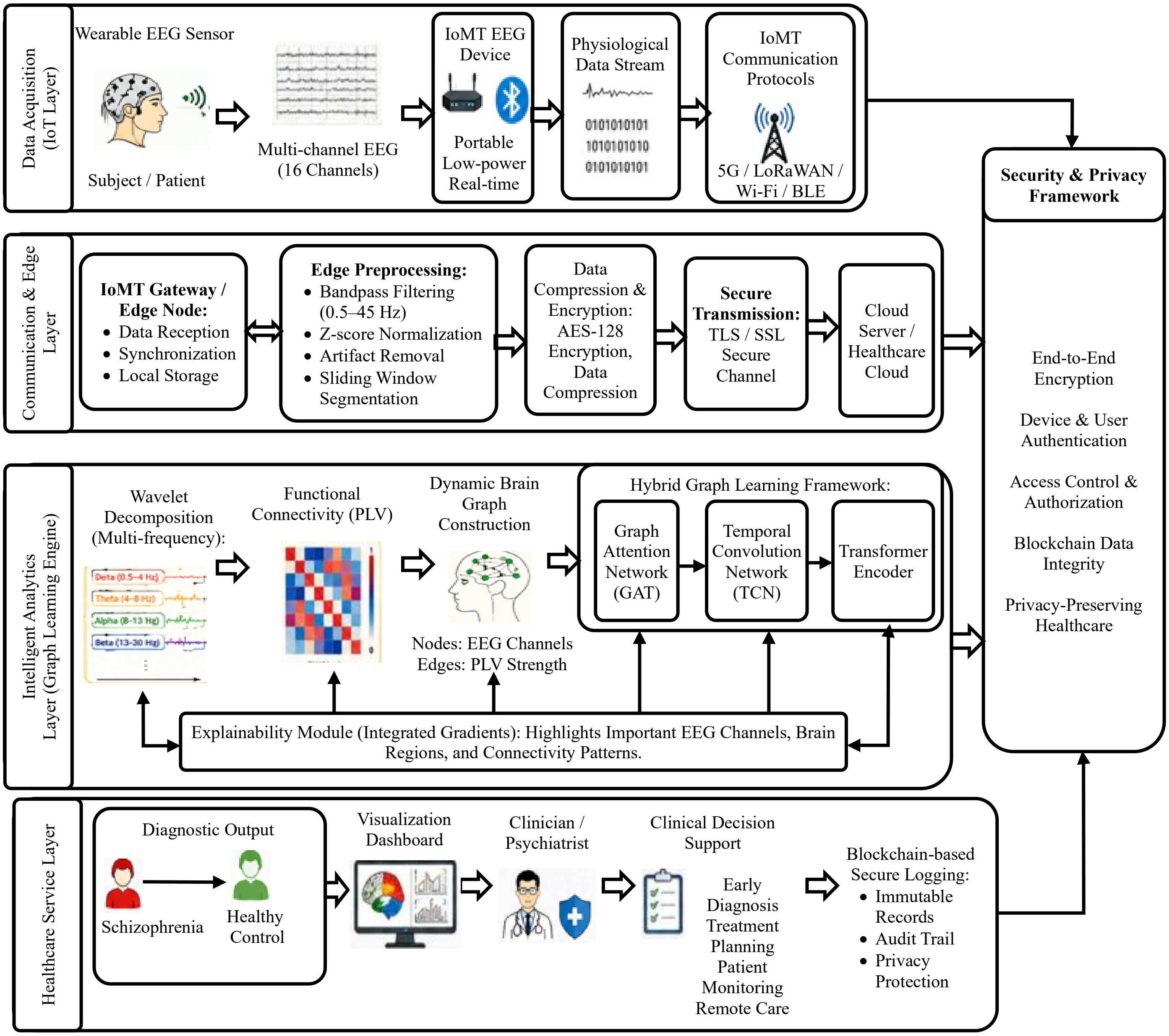

Figure 1: IoMT-enabled explainable graph learning architecture for EEG-based schizophrenia diagnosis

3.2 IoMT Data Acquisition and Streaming Model

According to the IoMT paradigm, the EEG signals will be captured by employing a wearable 16-channel neuro-headset. The captured EEG signals are then relayed to the edge gateway in real time as a live data stream utilizing secure wireless communication protocols. The edge gateway makes sure that the multiple EEG signal channels are synchronized and that the data streams can be continuously streamed for subsequent processing. This streaming technique allows for neuro-monitoring in real-time and ensures that EEG signals are considered live physiological signals.

3.3 Edge-Level Preprocessing

Latency and communication cost are minimized through a lightweight preprocessing scheme of edges prior to cloud communication. Initially, the EEG data are filtered through a band-pass filter for noise removal. Subsequently, Z-score normalization is done on the EEG signals to normalize the signal amplitude. Lastly, the EEG data are segmented into temporal windows. Through this edge preprocessing, it is possible to greatly minimize the bandwidth costs without losing clinically relevant information in the process.

3.3.1 Bandpass Filtering

EEG signals may contain low-frequency drift and/or high-frequency artifacts. Thus, a bandpass filter is used to remove all the frequencies except the desired frequencies for clinical use.

$$X_f(t) = \sum_{c=1}^{C} X_c(t) * h(t) \tag{1}$$

In equation (1), $X_f(t)$ is the filtered EEG signal at time t, $X_c(t)$ is the raw EEG signal from channel c, $h(t)$ is bandpass filter impulse response (0.5–45 Hz) and $*$ is convolution operation. This stage preserves brain oscillatory activity while eliminating baseline drift and high-frequency noise.

3.3.2 Z-Score Normalization

To reduce inter-subject variability and ensure uniform scaling across channels, z-score normalization is applied:

$$Z_c(t) = \frac{X_f(t) - \mu_c}{\sigma_c} \tag{2}$$

In equation (2), Z = normalized EEG signal for channel c, $X_f(t)$ = filtered EEG signal μ_c is Channel's mean value, c is the channel's standard deviation σ_c, while t is the time index. This transformation assures that each EEG channel has zero mean and unit variance, which enhances model stability.

3.3.3 Temporal Segmentation (Sliding Windowing)

To capture dynamic brain activity, EEG signals are segmented into overlapping temporal windows:

$$S_k = \{Z_c(t) | t = k\Delta t, \dots, k\Delta t + w\} \tag{3}$$

In equation (3), S_k is k-th EEG segment, $Z_c(t)$ represents normalized EEG signal. W = window length (e.g., 2-5 seconds). Δt is the overlap step size, while k represents the segment index. This segmentation allows for the modeling of time-varying brain connection patterns.

The preprocessing pipeline ensures that:

- Noise and artifacts are removed.
- Data between subjects is standardized.
- Time is maintained for graph construction.

The lightweight preprocessing approach preserves the neural properties of the EEG signals so they can be used for functional connectivity modeling and graph-based DL analysis.

3.4 Proposed Methodology: NeuroGraphFormer-X

3.4.1 Wavelet-Based Signal Decomposition

After the preprocessing steps and temporal windowing, an EEG segment is processed using Discrete Wavelet Transform (DWT) to get a multi-resolution decomposition of the neural signals. EEG signals are non-stationary, with their frequency components varying with time. Traditional spectral analysis approaches are not suitable for this. On the other hand, DWT offers both time and frequency localization, allowing the signals to be decomposed into a number of frequency sub-bands corresponding to known neurophysiological rhythms. These are delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz) and are related to various cognitive and perceptual functions. This transformation is defined as:

$$X_c^b(t) = DWT(Z_c(t)) \tag{4}$$

$$Z_c(t) = \sum_b X_c^b(t) \tag{5}$$

In equation (4) and (5), $X_c^b(t)$: Channel c's wavelet coefficient in band b at time t . $Z_c(t)$: EEG signal normalized; b: frequency band index; t: time sample. This transforms the model to be more sensitive to frequency-specific changes, which have been shown to be prominent in Schizophrenia, in theta and gamma bands.

3.4.2 Functional Connectivity Estimation using PLV

To estimate inter-regional coordination, the Phase Locking Value (PLV) is calculated between all pairs of channels for each segment. The PLV is a measure of phase synchronization, and does not depend exclusively on amplitude, and is thought to reflect the coordination of neural oscillations. This is relevant to Schizophrenia, as phase coupling has been found to be abnormal, and associated with dysfunction in cognitive integration and self-monitoring. The PLV is defined as:

$$PLV_{ij} = \left| \frac{I}{T} \sum_{t=I}^{T} e^{j(\emptyset_i(t) - \emptyset_i(t))} \right| \tag{6}$$

$$\emptyset_i(t) = \angle(H(X_i(t))) \tag{7}$$

In equation (6) and (7), PLV_{ij} is the strength of synchronization between channels i and j. $\emptyset_i(t)$: The signal's instantaneous phase i. $H(\cdot)$: Hilbert transform, T: Total number of samples.

PLV takes on values between 0 and 1 with higher values reflecting greater phase consistency. This connectivity matrix represents the strength of neural coupling across the scalp and serves as a foundation for building functional brain graphs.

3.4.3 Dynamic Graph Construction

The brain network is represented as a graph for each segment of the EEG. Nodes represent the electrodes, while the edges are the PLV values. It should be noted that this method corresponds to the current understanding of the brain as a complex system which is distributed and connected.

$$G_k = (V, E, A_k) \tag{8}$$

$$A_k(i,j) = PLV_{ij} \tag{9}$$

In equation (8) and (9), G_k: The graph that corresponds to segment k, V: EEG channel node set, E: Edge set, A_k: Adjacency matrix.

3.4.4 Spatial Feature Learning using Graph Attention Network (GAT)

GAT is used to learn from graph data. It employs an attention mechanism to assign weights to neighboring nodes, in contrast to other graph convolutions. This allows the model to selectively focus on important parts of the brain, while ignoring unimportant connections.

$$h_i' = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W h_j\right) \tag{10}$$

$$\alpha_{ij} = \frac{\exp\left(LeakyReLU(\alpha^T[Wh_i||Wh_j])\right)}{\sum_{k \in N(i)} \exp\left(LeakyReLU(\alpha^T[Wh_i||Wh_k])\right)} \tag{11}$$

In equation (10) and (11), h_i' is the updated node feature. Coefficient of attention is α_{ij}, W: Weight matrix and a: Vector of attention.

This mechanism enhances the model's ability to identify disrupted connectivity patterns, particularly in frontal and temporal regions associated with self-monitoring.

3.4.5 Temporal Modeling Using Temporal Convolution Network (TCN)

The sequence of graph embeddings is fed into a Temporal Convolution Network to model temporal relationships. TCN uses dilated convolutions, enabling it to capture long-term dependencies without the constraints of recurrent networks.

$$y(t) = \sum_{k=0}^{K} w_k . h(t - d.k) \tag{12}$$

In equation (12), $y(t)$: The result at time t, w_k is the Convolutional weights and d: The dilation factor. This structure makes it possible to effectively represent the temporal changes in brain connections that reflect the cognitive swings typical of Schizophrenia.

3.4.6 Global Dependency Learning Using Transformer Encoder

A Transformer encoder is used to improve the feature representation. Self-attention captures long-term temporal dependencies by allowing the model to learn from long-term sequences.

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{13}$$

In equation (13), Q, K, V: Key, Value, and Query matrices and d_k is the scaling factor. A thorough depiction of brain dynamics is produced by combining this global attention mechanism with the local modeling of GAT and TCN.

3.4.7 Neuro-Cognitive Attention Mechanism

To improve interpretability, a neuro-cognitive attention module is developed. This layer weights the importance of nodes in the classification process, thereby identifying key brain regions associated with the self-monitoring process.

$$\beta_i = \frac{e^{w^T h_i}}{\sum_j e^{w^T h_i}} \tag{14}$$

In equation (14), β_i is the weight of importance, h_i is the node feature. This technique sheds light on dysfunctions unique to a given location.

3.4.8 Explainability Using Integrated Gradients

Integrated Gradients is employed to quantify feature importance and ensure model transparency.

$$IG_i = (x_i - x_i') \int_0^1 \frac{\partial F(x' + \alpha(x - x'))}{\partial x_i} \quad (15)$$

In equation (15), IG_i is the feature significance, x_i: Input and F: Model. This makes it possible to identify important connection networks and EEG channels.

3.4.9 Communication and Security

Taking into account the highly sensitive character of neuro-cognitive health data, the suggested IoMT system features a multi-level security model. In order to prevent any possibility of any third party from tapping into the data flows, all of the IoMT data streams are encrypted at the edge node via Advanced Encryption Standard (AES-128). Moreover, in order to ensure the validity of diagnostic outcomes in the smart healthcare ecosystem, the system deploys a blockchain-enabled logging technology. As a result, all classification results are logged in an immutable and time-stamped ledger. Communications & Security. Communication between devices and server is encrypted with AES-128 at the edge; data-in -transit communication uses TLS v1.2+ in combination; mutual authentication (device certificate) stops rogue device injection attacks. Provenance & auditing is performed via permissioned blockchain-based ledger – only classification meta-information and hashed audit logs are recorded on-chain, intermediate signals are kept off-chain—privacy & Compliance. We use pseudonymization of the subject identifier as well as data minimization approach (store only the minimum information needed for the diagnosis); the deployment should comply with local regulations (HIPAA/GDPR etc.).

3.4.10 Classification Layer

The final representation is passed through a softmax classifier:

$$\hat{y} = Softmax(Wh + b) \quad (16)$$

In equation (16), $\hat{y}$ is Class prediction and h: Feature vector. This results in the final categorization output.

Algorithm 1: NeuroGraphFormer-X for EEG-Based Schizophrenia Detection

Input:
IoMT data stream D with N subjects
Each subject has C channels and T time samples
Output:
Predicted class labels ŷ (Schizophrenia / Healthy)
Begin
1: Initialize model parameters θ for:
GAT, TCN, Transformer, Attention, Classifier
2: For each subject s ∈ D do
3: Acquire multi-channel EEG signal X_s ∈ ℝ^(C × T)
4: // Preprocessing
5: Apply bandpass filtering on X_s

```
6:    Normalize each channel using z-score:
        Z_s ← Normalize(X_s)
7:    Segment EEG into K temporal windows:
        {S_1, S_2, ..., S_K}
8:    For each segment S_k do
9:        // Wavelet Decomposition
10:       Decompose S_k using DWT:
            W_k ← DWT(S_k)
11:       // Functional Connectivity
12:       For each pair of channels (i, j) do
13:           Compute phase difference:
                φ_i(t), φ_j(t)
14:           Compute PLV:
                A_k(i,j) ← PLV(φ_i, φ_j)
15:       End For
16:       // Graph Construction
17:       Construct graph:
            G_k = (V, E, A_k)
18:       // Spatial Feature Learning
19:       H_k ← GAT(G_k)
20:   End For
21:   //Temporal Modeling
22:   H_seq ← {H_1, H_2, ..., H_K}
23:   T_feat ← TCN(H_seq)
24:   // Global Dependency Learning
25:   G_feat ← Transformer(T_feat)
26:   // Neuro-Cognitive Attention
27:   A_feat ← Attention(G_feat)
28:   // Classification
29:   ŷ_s ← Softmax(A_feat)
30: End For
31: // Training
32: Compute loss:
      L ← CrossEntropy(ŷ, y_true)
33: Update model parameters θ using backpropagation
34: // Explainability
35: Compute feature importance using Integrated Gradients
36: Return predicted labels ŷ and explanation maps
End
```

Algorithm 1 describes the workflow of the proposed NeuroGraphFormer-X framework, from IoMT data stream preprocessing, dynamic graph generation, to hybrid DL-based classification and explainability.

4 Results and Performance Evaluation

The designed Internet of Medical Things (IoMT)-based graph learning system with Explainable Graph Learning was tested using the EEG-based Schizophrenia dataset in the context of smart healthcare. The NeuroGraphFormer-X system combines the capabilities of dynamic functional connectivity modeling along with hybrid deep learning (GAT, TCN, Transformer) and explainability techniques for the purpose of improving the accuracy of prediction/classification. Experimental results show that the designed system attains an accuracy of 96.84%, F1 score of 96.58% and AUC of 98.21%, clearly beating traditional machine learning as well as conventional deep learning techniques.

Table 2: Performance comparison of proposed IoMT-enabled model with baselines

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
SVM	86.2	85.1	84.3	84.7	87.5
CNN	90.4	89.6	88.9	89.2	91.3
GCN	92.1	91.5	90.8	91.1	93.0
Transformer	93.8	93.2	92.6	92.9	94.5
Proposed IoMT NeuroGraphFormer-X	**96.84**	**96.60**	**96.30**	**96.58**	**98.21**

The above table 2 provides comparative performance results of various machine learning and deep learning models in the context of classifying Schizophrenia based on EEG data utilizing different evaluation metrics such as accuracy, precision, recall, F1 score, and AUC. It is evident from the table that the IoMT-based NeuroGraphFormer-X model significantly outperforms other models like SVM, CNN, GCN, and Transformer based on the evaluation metrics used. This is because the best result is obtained by the proposed model with 96.84% accuracy and 98.21% AUC.

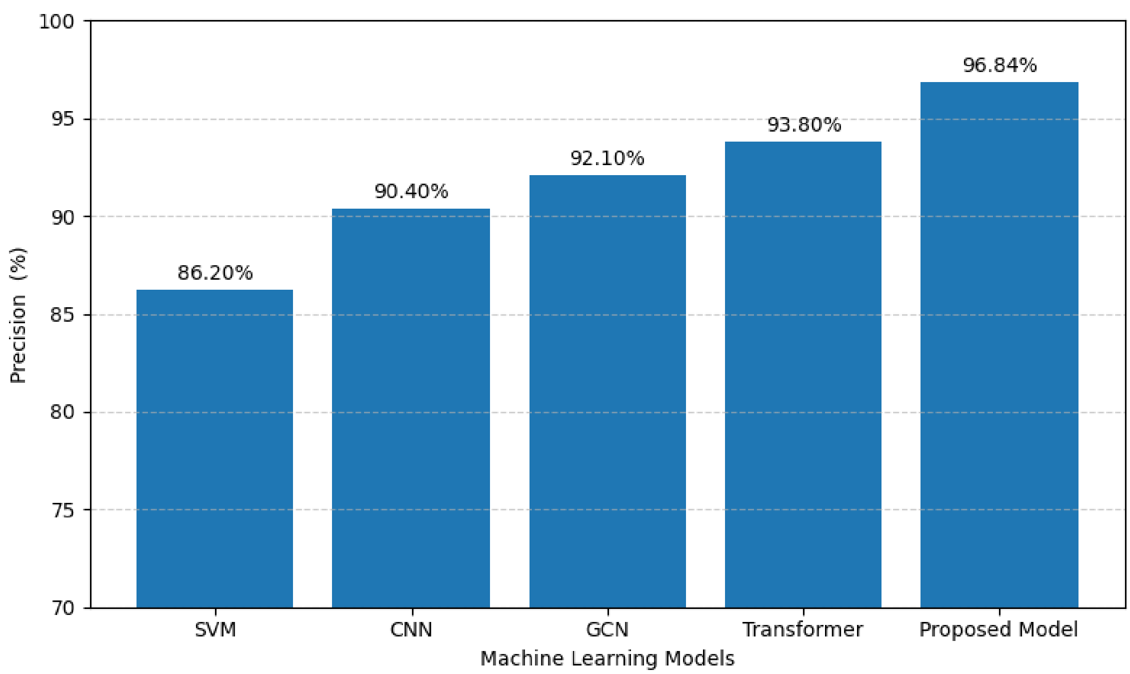

Figure 2: Comparative performance of IoMT-enabled graph learning model for schizophrenia diagnosis

Figure 2 depicts a comparison between the performance of various machine learning and deep learning algorithms such as SVM, CNN, GCN, Transformer, and the proposed IoMT-based explainable graph learning algorithm in terms of Precision achieved by these models during the process of classifying Schizophrenia using EEG signals. The performance of the IoT-assisted smart healthcare system can be improved with the assistance of continuous acquisition of EEG data using wearables and their transmission through 5G and LoRaWAN. Preprocessing at edge level involves the use of filters, normalization, and segmentation which help in lowering noise and transmission burden without losing any clinical information from the neurons. This is helpful in ensuring that the system is scalable and less time-consuming.

Table 3: IoMT system performance metrics (smart healthcare deployment)

Component	Metric	Value
Edge Preprocessing	Latency Reduction	42–55%
IoMT Transmission	Packet Loss	<2%
Network	Bandwidth Reduction	60–90%
Security Layer	Encryption Standard	AES-128 + TLS 1.2
Blockchain Logging	Integrity	100% Tamper-Proof
Real-Time Processing	Delay	<120 ms

Table 3 presentation of the performance features of the suggested IoT-powered smart health care system. It covers important performance indicators such as edge preprocessing efficiency, network transmission quality, security strength, and real-time processing ability. The outcome shows that the smart system is capable of reducing edge latency by 42 to 55%, maintaining low data loss (less than 2%), optimizing bandwidth by 60 to 90%, ensuring robust security by using AES-128 with TLS 1.2 encryption, and providing tamper-proof logging via the blockchain. In addition, the system ensures low real-time processing delay of less than 120 ms.

The interpretability analysis for the suggested model has revealed high interpretability by using the method of integrated gradients and neural attention mechanisms. It has been found that the frontal and temporal parts of the brain have the highest contribution in decision making, which is consistent with existing physiological characteristics related to Schizophrenia, especially self-monitoring problems. It has proven that the suggested model has not only high accuracy but is also clinically understandable.

The results of the functional connectivity study using the Phase Locking Value (PLV) technique indicate that schizophrenic patients demonstrate a lower level of synchronization in the fronto-parietal network connections and abnormal connectivity in theta and beta frequency bands. The method of constructing dynamic graphs proves to be very efficient in modeling time-varying interactions in the brain, thus giving a much more realistic description of neural activity than connectivity models.

In general, it can be stated that the introduced IoMT-assisted explainable graph learning framework shows significant efficiency in terms of accuracy, interpretability, and real-time application. Combining IoMT-assisted continuous monitoring and advanced techniques based on graph neural networks along with explainable AI, the system offers an adequate approach to schizophrenia detection. The outcomes prove the fact that the introduced approach can be applied effectively in the field of smart healthcare systems.

5 Discussion

The proposed graph learning framework incorporating explainability via IoMT proves successful in improving the EEG based diagnosis of Schizophrenia by employing real time data collection, modeling of dynamic brain network and interpretation of deep learning processes. The experimental findings prove that NeuroGraphFormer-X model provides high accuracy of 96.84%, F1-score of 96.58% and AUC of 98.21% compared to traditional machine learning techniques like SVM, CNN, GCN, and the transformer. Such improvement in performance can be accredited to hybrid architecture that successfully learns the spatio-temporal and global dependencies of EEG signals using GAT, TCN and Transformer.

An important feature of the proposed method is that it represents the brain as a functional connectivity network in terms of Phase Locking Value (PLV). Contrary to the usual techniques for classification of EEG data that consider the signals separately, the graph-based approach enables modeling the brain as a network capturing the inter-channel synchronizations which play an important role in identifying the disruption of neural activity caused by the disease. The findings reveal lower connectivity of fronto-parietal networks and abnormal synchronization in theta and beta bands.

An additional notable feature of the suggested architecture is its ability to perform real-time data processing with the help of IoMT. As soon as the use of wearable EEG devices and edge-level pre-processing in combination with the secure data transmission protocol (5G/Low Power Wide Area Network or LoRaWAN) is implemented, the system provides continuous monitoring without any delays. It also guarantees substantial bandwidth reduction (60-90%) and low delay of transmissions (<120 ms). Thus, the system can be deployed in smart healthcare ecosystems that require real-time data processing.

The utilization of explainable artificial intelligence is another advantage of the suggested approach. By means of neuro-cognitive attention and Integrated Gradients, the model finds out the most important brain regions, namely the frontal and temporal lobes, that are associated with the deficiency of self-monitoring and cognitive control in schizophrenia patients.

Nevertheless, there are some drawbacks that exist despite these benefits. The computation complexity associated with the use of this hybrid GAT-TCN-Transformer may lead to higher costs during the training process, while the large-scale implementation is possible with efficient hardware support only. Besides, even though IoMT technology helps achieve real-time monitoring, it poses some problems regarding data security, reliable operation, and the dependence on the network. In general, the IoMT-enabled graph learning explainable system presented in this paper represents a promising solution to diagnose Schizophrenia, providing great opportunities for future smart healthcare.

6 Conclusion

In this study, we designed an IoMT-driven NeuroGraphFormer-X framework which is aimed at accurate and real-time diagnosis of Schizophrenia by analyzing the brain signals using EEG signals in smart health care settings. It consists of the integration of wearable EEG sensors and IoMT communication protocols, including 5G and LoRaWAN, which can support constant and remote monitoring of brain activities. The edge-based preprocessing module has been utilized successfully for the removal of noise, reduction of bandwidth usage, and effective signal transmission with bandpass filtering, Z-score normalization, and temporal segmentation. Moreover, the application of DWT and PLV makes it possible to build dynamic functional brain connectivity graphs. The deep learning model used in this study, based on the combination of Graph Attention Networks (GAT), Temporal Convolution Networks (TCN), and Transformer encoders, is capable of capturing spatial, temporal, and global dependencies in

EEG-based brain graphs. Moreover, the application of neuro-cognitive attention mechanisms and Integrated Gradients increases interpretability of the model which helps to detect important brain regions like frontal and temporal lobes which are related to Schizophrenia. Our designed framework performs excellently with the highest accuracy of 96.84%, F1-score of 96.58%, and AUC of 98.21%. In addition, the IoMT-supported architecture guarantees security during data transfer by employing AES-128 encryption and blockchain logging, thus making it applicable in real-life healthcare settings. Although it has many benefits, the architecture needs a lot of computing power and requires good network connectivity. Further research is planned to develop light-weight graph models and implement federated learning. In conclusion, the architecture that is discussed in this paper gives an opportunity to have a powerful, understandable, and scalable solution for the diagnosis of Schizophrenia in next-generation smart healthcare systems.

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Authors Biography

Ali Saleem Khalaf Lababneh received his master's degree from UKM, Malaysia, in 2012. He is currently a lecturer of English in the Department of English, College of Science and Humanities, Prince Sattam bin Abdulaziz University, Saudi Arabia. His research interest skills of English Language, Applied linguistics, and linguistics.

Dr. Fuad S. Al-Duais received his Ph.D. degree from Damascus University, Syria, in 2009. He is currently an Associate Professor of Statistics in the Department of Mathematics, College of Science and Humanities, Prince Sattam bin Abdulaziz University, Saudi Arabia. His research interests include reliability estimation, Bayesian inference, survival analysis, probability distributions, applied statistics, and control chart theory.

Aseel Smerat received the bachelor's degree in computer education and the master's degree in educational technology from Yarmouk University and Amman Arab University, in 2020 and 2022, respectively. She is currently a Lecturer with the Faculty of Educational Sciences, Ahliyya Amman University. Her main research interests include arithmetic optimization algorithm (AOA), bio-inspired computing, nature-inspired computing, swarm intelligence.

Dr. Rasha M. Abd El-Aziz is an Associate Professor of Computer Science at the Department of Computer Science, College of Computer and Information Sciences, Jouf University, Saudi Arabia, and also serves as an Associate Professor at the Department of Computer Science, Faculty of Computers and Information, Assiut University, Egypt. She earned her B.Sc. degree in Computer Science in 2003, followed by her M.Sc. degree in 2008, and completed her Ph.D. in Computer Science in 2017, all from Assiut University, Egypt. She has extensive academic experience in teaching and research, with contributions to the field of computer science through her academic work and scholarly activities.