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ARTICLE

Explainable Hybrid Deep Learning for Secured Seizure Detection Framework Based on EEG Signal in Medical IoT Systems

Ezz El-Din Hemdan[1], Haitham Elwahsh[2,3], Samah Alshathri[4,*] and Amged Sayed[5,6,*]

[1]Department of Computer Science and Engineering, Faculty of Electronic Engineering, Menoufia University, Menouf, 32952, Egypt
[2]Cyber Security and Cloud Computing Department, Faculty of Information Technology, Applied Science Private University, Amman, 11931, Jordan
[3]Department of Computer Science, Faculty of Computers and Information, Kafrelsheikh University, Kafrelsheikh, 33511, Egypt
[4]Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh, 11671, Saudi Arabia
[5]Department of Electrical Energy Engineering, College of Engineering & Technology, Arab Academy for Science Technology & Maritime Transport, Smart Village Campus, Giza, 12577, Egypt
[6]Industrial Electronics and Control Engineering Department, Faculty of Electronic Engineering, Menoufia University, Menouf, 32952, Egypt

*Corresponding Authors: Samah Alshathri. Email: sealshathry@pnu.edu.sa; Amged Sayed. Email: amged.sayed@aast.edu

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ABSTRACT: Ensuring robust methods for maintaining high levels of medical data security is crucial in the Medical Internet of Things (IoT) for the protection of sensitive patient data during real-time transmission and analysis. Electroencephalography (EEG) signals in medical IoT systems are transmitted through cloud and edge networks, which create risks of cyber threats, unauthorized access, and data breaches. Consequently, there is an urgent need for efficient encryption methods to ensure the confidentiality of EEG signals during classification and prediction processes, as several state-of-the-art models either neglect security during classification or suffer from increased computational overhead that limits real-time applicability. In this paper, an innovative framework is proposed for secured and accurate detection of seizures from EEG signals based on Quantum Hilbert Encryption-assisted hybrid deep learning and machine learning methods. Raw EEG signals are first converted into 2D spectrogram images to facilitate visual feature analysis. These spectrogram images are then encrypted using the newly developed Quantum Hilbert Encryption Scheme to preserve the sensitive medical data while processing or transmission occurs. In addition, deep learning methods used encrypted EEG representations to extract discriminant features while maintaining the signal integrity and data confidentiality. Then, machine learning classifiers are used for seizure classification, efficiently and accurately doing so. Experimental evaluations highlight the system's strong performance: Support Vector Machine (SVM) achieved top accuracies of 87.63% with ResNet50 as features extractor and 83.51% with VGG19 as feature extractor, while RF excelled in precision with scores of 88.61% (SVM with ResNet50 as features extractor) and 87.91% (RF with Xception as features extractor). These results confirm the system's superior capability in seizure detection using encrypted EEG data. To enhance model interpretability, we employed Gradient-weighted Class Activation Mapping (Grad-CAM) and Local Interpretable Model-agnostic Explanations (LIME) to visualize and explain the decision-making process of the proposed hybrid AI model. By combining cutting-edge encryption with hybrid AI models and Explainable AI, the proposed method holds promising potential for application in Medical IoT (MIoT) environments, where secure real-time automatic EEG analysis is paramount.

KEYWORDS: Seizure detection; electroencephalography (EEG) signals; Transfer Learning (TF); Gradient-weighted Class Activation Mapping (Grad-CAM); Local Interpretable Model-agnostic Explanations (LIME); quantum Hilbert encryption; deep learning; medical IoT

1 Introduction

Recently, researchers have shown significant interest in Quantum Processing (QP) due to its superior efficiency, robustness, and security compared to classical information processing. This has notable technological implications for communication systems, cybersecurity, and multimedia processing. Quantum Image Processing (QIP), which applies quantum computation to store, manipulate, and recover digital images, enhances performance and efficiency by converting digital image information into quantum representations for faster processing [1]. Quantum information is particularly beneficial in image processing, where quantum parallelism accelerates tasks such as quantum image encryption, quantum watermarking, and steganography. Lately, there has been an increasing focus on multimedia security via quantum encryption, as secure transmission of multimedia data over unsecured networks often relies on scrambling algorithms [2,3].

In the field of digital image classification and analysis, convolutional neural networks (CNNs) enable efficient processing for automatically extracting features and interpreting structured data from digital images for various applications [4–6]. To expand the scope of encrypted image classification, AI models have been developed that consider the practical simplicity of images derived from EEG signals. The typical data analysis workflow for encrypted EEG image recognition comprises four key stages, as illustrated in Fig. 1:

1. Creating a Digital Image Database: This stage involves using image acquisition tools, such as a camera setup, to create a comprehensive digital image database.
2. Image Preprocessing and Feature Extraction: If necessary, apply preprocessing techniques like image segmentation to slice the region of interest within the images in the dataset. Also, extract features from the digital images to capture relevant information for classification.
3. Model Selection: Utilize AI models, including machine learning and deep learning models, to analyze the extracted features and achieve optimal image classification results.
4. Model Evaluation: Evaluate and assess the models to select the best-performing one for deployment in the field.

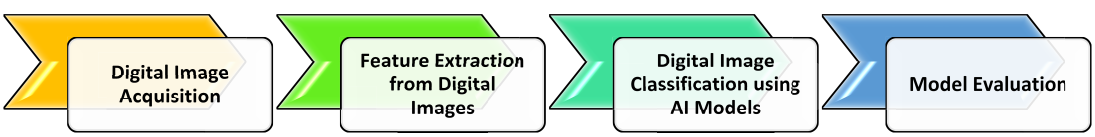


Figure 1: A conventional AI-based digital image identification.

Disease classification and prediction in telemedicine applications might be greatly advanced by the development of artificial intelligence (AI), Cloud Computing (CC), and the Internet of Things (IoT). The rapid advancement of deep learning in healthcare, particularly for diagnosing epileptic seizures via EEG signals, has facilitated the effective identification of such seizures. Lately, IoT and medical systems have become complementary technologies that together provide significant advantages for a range of MIoT applications [7]. Real-time monitoring, analysis, and decision-making inside intricate healthcare systems are made easier by the integration of medical services with IoT devices. The MIoT system consists of several levels, as Fig. 2 illustrates:

- Level 1: MIoT sensors and actuators are applied in this level for of gathering and keeping track of different types of medical and healthcare data.
- Level 2: The sensor network is connected to cloud servers via gateway and edge devices, which act as middlemen. The MIoT-based controller platform would not function without these devices.
- Level 3: Intelligent medical IoT solutions are driven by cloud computing at this level. Medical data collected by the MIoT-based controller is stored and processed on cloud computing servers. Using an IoT protocol such as Constrained Application Protocol (COAP), the gathered data is regularly sent to the relevant channel.
- Level 4: The development of web and mobile applications that communicate with cloud servers to retrieve analytical results is the main focus of this level. When machine learning algorithms are applied to stored medical and healthcare data, these results are produced. The main goal is to give healthcare organisations useful information for making decisions.

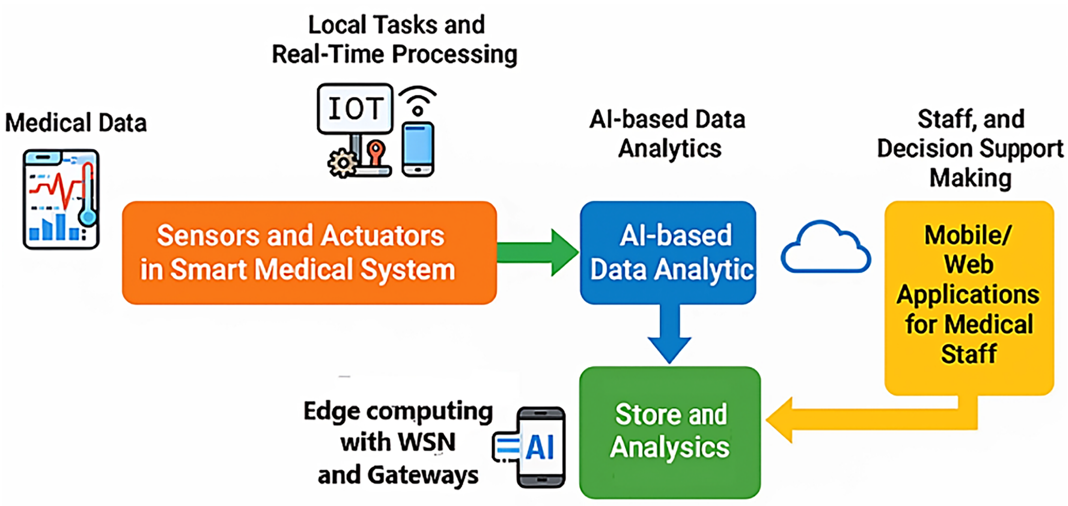


Figure 2: A typical smart medical IoT architecture.

In general, the Medical IoT system's multitier design facilitates a seamless flow of data, storage, and analysis. Providing healthcare and medical facilities with up-to-date data enables them to make educated decisions that optimize their medical operations. The incidence of seizure detection is rising due to several variables, including solar exposure patterns, longer life expectancies, and early identification of the disease.

An EEG-based IoT application framework is intrinsically susceptible to serious assaults since the attacker can modify the EEG data while it is being communicated via unprotected networks and can listen to the channel and collect the data being transmitted without changing it [8]. For example, if a hospital wants to use a cloud service to predict a patient's likelihood of having epilepsy, it must make precise predictions while guaranteeing the security and confidentiality of the data that is delivered. As a result, efficiently handling encrypted EEG data has grown increasingly difficult. In order to overcome these security issues, several researchers have started concentrating on the use of encryption techniques in the field of machine learning [9].

The pressing security issues in IoT networks drive the need for a superior system that exceeds current solutions in terms of classification accuracy, implementation efficiency, and data safety and privacy. In this paper, we introduce a novel approach for the encrypted classification and recognition of EEG signals, combining quantum Hilbert encryption algorithms with hybrid deep learning techniques. First, EEG signals are converted into 2D spectrogram images and then encrypted before undergoing feature extraction and selection through deep learning models. Subsequently, machine learning models are employed to achieve effective classification and prediction.

This paper tackles several critical gaps in existing research by providing an effective framework for encrypted classification of EEG signals, establishing high security along with high accuracy in classification performance. By leveraging the advanced encryption techniques and machine learning algorithms, this system comes as a strong framework for medical professionals all around the world to aid and assist in diagnosis regarding seizures at an earlier stage while maintaining data confidentiality as well as predictive accuracy. Therefore, the key contributions of this work can be summarized as follows:

- To help, assist, and empower doctors worldwide in securely diagnosing seizure detection at an early stage.
- Utilizing a hybrid CNN-based classification methodology, which combines CNN models with machine learning classifiers, demonstrates superior outcomes and performance compared to conventional techniques for secure seizure detection. This approach also facilitates the development of a new real-time Medical IoT system for seizure detection in an effective manner.
- From the results, SVM achieves top accuracy with scores such as 87.63% (ResNet50) and 83.51% (VGG19), while RF excels in precision with results like 88.61% (SVM with ResNet50) and 87.91% (RF with Xception). These findings affirm their effectiveness in seizure detection using encrypted EEG data.
- The introduction of Explainable artificial intelligence (XAI) via Grad-CAM and LIME makes it possible to interpret and depict seizure detection decisions from quantum-encrypted EEG inputs, providing transparency and trust to the proposed hybrid model.

The structure of the paper is as follows: Section 2 introduces the preliminaries of the Teager energy operator and the quantum Hilbert encryption algorithm, while Section 3 reviews previous studies related to the paper's subject. Section 4 describes the proposed system, and Section 5 presents the analysis of results and discussion. Section 6 shows a High-Level IoT-based Privacy-Preserving Seizure Detection System, while Section 7 provides the conclusion and future scope of this innovative theme.

2 Prefaces

This section introduces the foundational concepts for this research, focusing on the Teager-Kaiser Energy Operator and quantum Hilbert algorithms.

2.1 Teager-Kaiser

One of the most significant nonlinear energy tracking operators is the Teager-Kaiser Energy Operator (TKEO) to represent the discrete form of the Teager Energy Operator. It can determine the instantaneous energy of a non-stationary signal and can track both the frequency and the instantaneous amplitude of a signal. While the Hilbert Transform (HT) is typically used to separate amplitude and frequency over a broad range, TKEO excels in efficiently separating local amplitude and frequency fluctuations. The sensitivity to amplitude and frequency modulation is one of the most impressive assets of TKEO, capable of expertly picking up transient aspects of signals, such as rapid changes or sudden bursts of energy. This has led to its growing popularity in many different fields, such as biomedical applications, analyzing physiological signals like EEG and electrocardiogram (ECG). Micro-change detection is also used within mechanical systems, enabling machinery condition monitoring by analyzing vibration patterns to identify faults. The TKEO for a continuous signal $g(t)$ is defined as follows [10]:

$$\Psi\left(g(t)\right) = \dot{g}(t) - g(t)\ddot{g}(t) \tag{1}$$

For a discrete signal, by substituting the derivatives with their time differences, the TKEO for a discrete sequence $g\,[n]$ is defined as follows [11]:

$$\Psi(g[n]) = g^2[n] - g[n-1]g[n+1] \tag{2}$$

In Eq. (2), only three samples are necessary to calculate the energy of a signal at any given instant. Consequently, the energy operator possesses several features that make it highly effective for signal processing applications. These features include a small-time window, simplicity, and ease of implementation.

Modern applications are still witnessing the development of TKEO as it integrates with enhanced signal processing frameworks, such as EEG image classification. The TKEO has also been useful in brain signal activity for identifying minor alterations in neural activity and energy patterns that usually indicate certain mental states or neurologic disorders. Because of its transience-localization feature, it is highly capable of discriminating between different classes of EEG signals, such as those concerning sleep stages, seizure detection, or cognitive load. These several applications prove the operator's versatility and timeless value in progressing EEG-based diagnostics and understanding brain dynamics further. In this paper, TKEO is used to differentiate between healthy and seizure EEG signals [12].

2.2 Quantum Hilbert Image Scrambling

Quantum algorithms are stepwise subroutines that are carried out on a quantum computer to leverage quantum mechanical phenomena. Some of these algorithms are applied to perform computations in a large Hilbert space memory structure efficiently over classical algorithms [13]. Quantum Hilbert Image Scrambling converts the encoding information procedure into a quantum state as a feature mapping of the input data into the Hilbert space of the quantum system.

In this work, the quantum Hilbert algorithm is utilized to encrypt the spectrogram images generated from the EEG signal [14]. In the Hilbert Image Scrambling method, a quantum technique is provided to scramble a quantum image. The input is a 2n × 2n original image, and the output is the Hilbert scrambled quantum image. The images are represented using Flexible Representation for Quantum Images (FRQI).

To represent images on quantum computers, the flexible representation for quantum images (FRQI) was proposed in [15,16]. The typical quantum image representation can be described by the subsequent equations:

$$|I_\theta\rangle = \frac{1}{2^n}\sum_{j=0}^{2^k-1} |\Delta_j\rangle \otimes |\,j\rangle\,,\, where\ k = 2n\,(the\ size\ of\ quntum\ image) \tag{3}$$

$$|\Delta_j\rangle = \cos\theta_j|\,0\rangle + \sin\theta_j|\,1\rangle\,,\theta_j \in \left[0, \frac{\pi}{2}\right], j = 0, 1, \ldots, 2^k - 1 \tag{4}$$

where θ_j is the vector of angles encoded colors, $|0\rangle, |1\rangle$ are 2-dimension quantum states.

The relation that explains the vertical and horizontal coordinates for $|\Delta_j\rangle$, which represents color information at a matching position in the image $|j\rangle$, is as obeys:

$$|j\rangle = |\,Y\rangle|X\rangle = |Y_{n-1}Y_{n-2}\ldots Y_0\rangle|X_{n-1}X_{n-2}\ldots X_0\rangle \in 0, 1 \tag{5}$$

For every $j = 0, 1, \ldots, n-1$, encodes $|Y\rangle$ along the vertical location and $|X\rangle$ along the horizontal location.

One of the crucial matrices in image scrambling is the Hilbert scanning matrix which will rearrange each pixel to a new position, and is conferred by the succeeding equation:

$$\Gamma_{n+1} = \begin{cases} \begin{pmatrix} \Gamma_n & \Gamma_n^T + 4^n \mathrm{M}_n \\ \left(4^{n+1}+1\right)\mathrm{M}_n - \Gamma_n^{ud} & \left(3\times 4^n + 1\right)\mathrm{M}_n - \left(\Gamma_n^{lr}\right)^T \end{pmatrix}, & n\ is\ even \\ \begin{pmatrix} \Gamma_n & \left(4^{n+1}+1\right)\mathrm{M}_n - \Gamma_n^{lr} \\ \Gamma_n^T + 4^n \mathrm{M}_n & \left(3\times 4^n + 1\right)\mathrm{M}_n - \left(\Gamma_n^T\right)^{lr} \end{pmatrix}, & n\ is\ odd \end{cases} \tag{6}$$

where $\Gamma_n \in \mathbb{R}^{2^n \times 2^n}$ denote the Hilbert matrix at recursion level n. The matrix $M_n \in \mathbb{R}^{2^n \times 2^n}$ represents an all-ones matrix of compatible dimension. The operators $(\cdot)^T$, $(\cdot)^{ud}$, and $(\cdot)^{lr}$ denote the transpose, upper-down block extraction, and lower-right block extraction, respectively. At each recursion level, the matrix dimension doubles, generating Γ_{n+1} from four transformed submatrices derived from Γ_n. And n is a positive integer, the initial matrices are:

$$\Gamma_1 = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix}$$

and

$$M_n = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & & 1 \\ \vdots & & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{pmatrix}$$

The recursive generation algorithm in Hilbert scrambling can be divided into three basic operations: initialization, odd, and even. Knowing even and odd are carried out alternately [14]. The process can be described in Fig. 3.

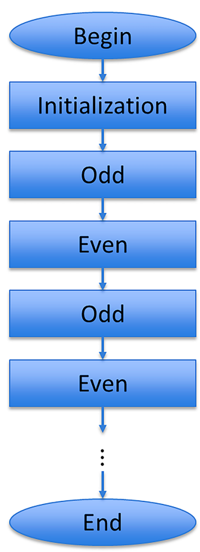


Figure 3: Flowchart of recursive generation algorithm.

The integrated Hilbert image scrambling quantum circuit is shown in Fig. 4. The meaning of the final basic circuit Even $(n-1)$/Odd $(n-1)$ is that if $n-1$ is an even number, the final basic circuit is Even $(n-1)$; otherwise, it is Odd $(n-1)$ [14]. The recursive traversal and gate application steps account for most of the computational complexity. Encryption and decryption increase inference latency by just 3%–5%, making it acceptable for real-time IoT-based medical applications.

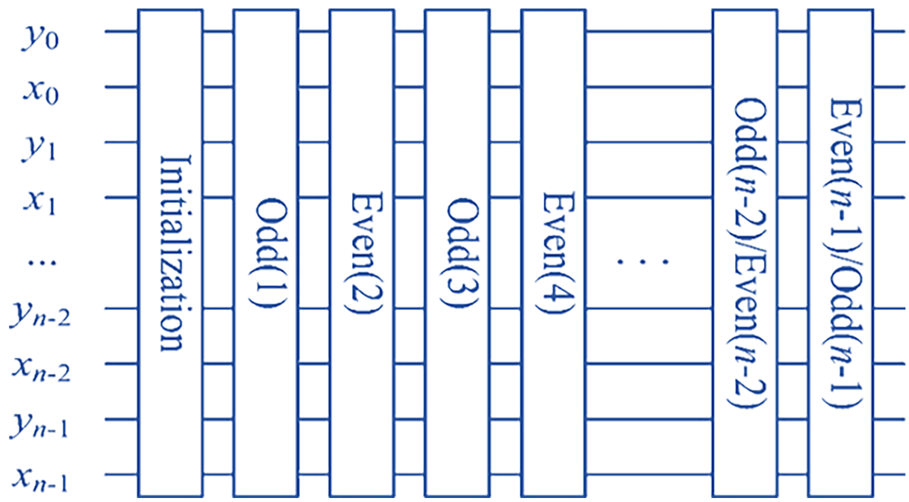


Figure 4: Integrated Hilbert image scrambling quantum circuit.

3 Previous Studies

In recent years, considerable attention has been focused on the classification and modeling of EEG data. Electroencephalography has emerged as a key tool for remote epileptic seizure recognition, resulting in the development of various methods for early epilepsy analysis using EEG signals.

Recently, the classification of encrypted EEG data has gained increasing importance. In [17], a method for secure cloud searching tasks using an Extreme Learning Machine (ELM) was proposed, though it involves high time complexity. In [18], the benefits of Convolutional Neural Networks (CNNs) were combined with Fully Homomorphic Encryption (FHE) for privacy-preserving purposes. A method for importing learnt neural networks into CryptoNets was introduced in [19]. In Internet of Medical Things (IoMT) security, traditional ring signature schemes face limitations in dynamic multi-party participation, and entity-specific permissions is presented in [20]. It addressed these challenges through a dual-ring sequential multi-signer framework with formal security guarantees and substantially reduced computational and storage overhead.

With an accuracy of 78.2%, a novel Sparse Group Representation Model (SGRM) presented by [21] effectively classifies data for motor imagery-based Brain-computer interface (BCI) applications by utilising intersubjective data. SVM and ensemble classifiers are used to help evaluate the accuracy of the Fuzzy Discernibility Matrix (FDM), which is used in [22] to extract the best features from EEG signals. Nevertheless, this approach has trouble with multi-classification issues and huge EEG datasets. A GTDA-based epileptic seizure detection approach introduced in [23] analyzes EEG signals through Wavelet Transform to construct spatial–spectral–temporal tensors, from which discriminative features are extracted and classified using K-Nearest Neighbors (KNN), achieving a 98% detection rate with an average delay of 4.7 s. Authors in [24] proposed B2-ViT Net, a novel bi-level programming framework that integrates broad attention Vision Transformers to capture global spatial channel interactions and long-range temporal dependencies for seizure prediction. In order to process EEG signals and extract features via amplitude estimation, the Coiflets wavelet was employed in [25]. By combining Discrete Wavelet Transform and Bayesian-optimized deep learning within an IoMT framework, a novel Convolutional Learning Attention-Bidirectional Time-Aware LSTM (CL-ATBiLSTM) model proposed in [26] successfully classifies EEG data into Alzheimer's disease, Mild Cognitive Impairment, and healthy control groups with an accuracy of 96.52%. A homomorphic encryption scheme that supports addition and multiplication was introduced in [27]. A secure multiparty computing paradigm was used in [28] to preserve data privacy.

The combination of Grad and LIME enhances disease detection models by improving both accuracy and interpretability. The combination of Gradient Boosting and LIME enhances disease detection models by providing interpretable recommendations, allowing for better understanding of feature importance, and improving trust in predictions, ultimately leading to more accurate and personalized medical recommendations for patients [29]. The integration of Grad and LIME has been successfully applied in diagnosing diseases like Alzheimer's and cardiovascular conditions, showcasing its versatility and effectiveness in real-world scenarios [30].

Therefore, finding methods that guarantee minimal overhead and high precision in encrypting EEG data remains a challenging issue. This study aims to propose an effective scheme for seizure detection and prediction involving three precise phases, as illustrated in Fig. 5. The steps are as follows:

1. EEG Image Collecting Stage (EICS)
2. Feature Extraction Stage (FES)
3. Seizure Prediction Stage (SPS)

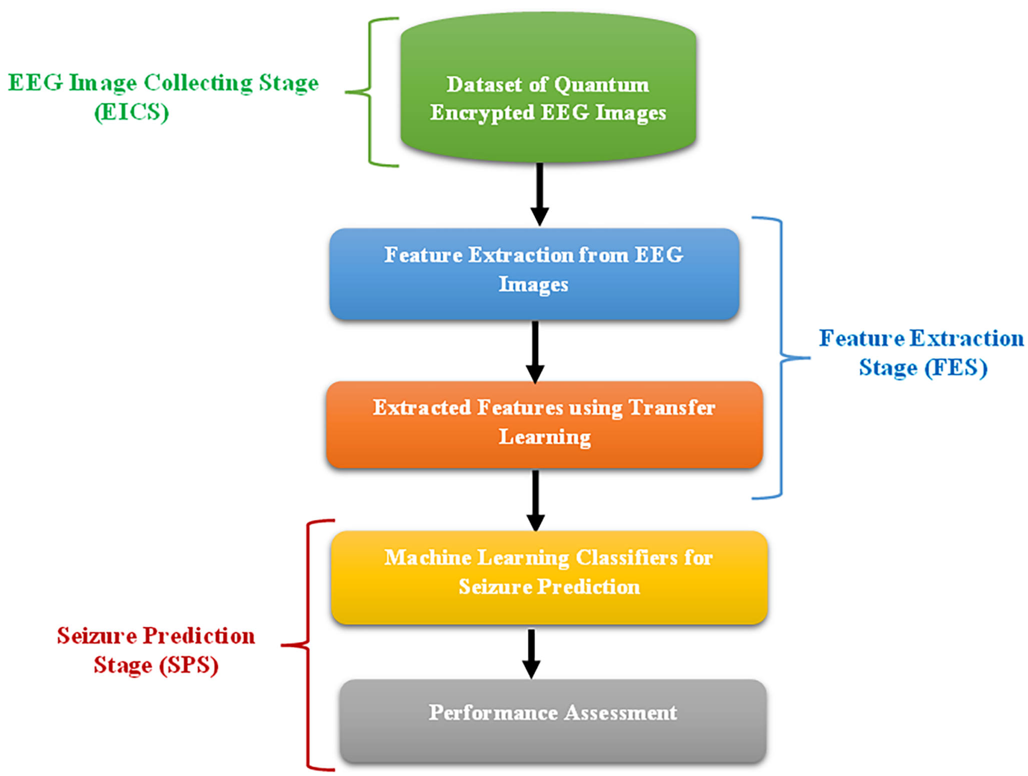


Figure 5: Proposed seizure prediction system.

This method aims to develop an intelligent, secure seizure prediction system for smart medical applications. The subsequent system provides a model for seizure detection and classification. Likewise, this work presents an efficient hybrid framework based on deep learning techniques for feature selection from EEG spectrogram images and their classification using machine learning models. The detailed proposed system consists of the following phases:

Stage 1: This stage involves collecting EEG image data from Medical IoT Systems.

Stage 2: Applies preprocessing techniques to the EEG spectrogram image dataset, focusing on feature extraction using Transfer Learning models.

Stage 3: Develop a machine learning classifier using the extracted features from quantum-encrypted EEG to effectively predict seizures based on the features identified in the previous stage.

4 Proposed Seizure Detection System

This section describes the offered hybrid deep learning framework for seizure detection. The major phases of the proposed framework are displayed in Fig. 6. To evaluate the feasibility of our proposed strategy for medical care applications in recognizing epileptic seizures using encryption techniques based on EEG recordings, we conducted experiments using the publicly available CHB_MIT dataset [31]. Both use cases were framed as binary classification tasks, where seizures are represented by 1 and normal activity by 0. The research focused on applying the proposed strategy to encrypted spectrogram EEG data. Given the privacy concerns associated with collecting EEG data for model training or transmitting it to model owners for inference, our investigations explored various approaches to EEG signal encryption. We utilized pretrained CNNs for feature extraction because the CHB-MIT dataset had a limited size which led to overfitting and training instability. The proposed system utilizes the classical classifiers to analyze the extracted features because these methods provide better explanations of results and enable precise testing between different classifiers while decreasing the required processing time. The hybrid method has been applied to give good results when used in biomedical signal analysis. A detailed description of the proposed system is as follows:

1. **Transformation of EEG Signals into Spectrograms:**
   - The Electroencephalography (EEG) signals, which are time-series data, transform into two-dimensional (2D) spectrograms.
   - This transformation employs the Teager Energy Operator (TEO), a technique that highlights the energy variations in the signal more effectively.
   - The primary objective of converting EEG signals into spectrograms is to capture additional texture details and intricate features that are not easily discernible in the raw EEG data. These enhanced features are crucial for improving the accuracy of seizure prediction.
2. **Encryption of EEG Images:**
   - Once the EEG signals are transformed into spectrograms, these 2D images are subjected to encryption.
   - The encryption process uses Quantum Hilbert Permutation, a method designed to secure EEG images by scrambling them in a sophisticated manner.
   - The output of this process is a set of encrypted EEG images, which ensures the privacy and security of the data during subsequent processing stages.
3. **Feature Extraction Using Transfer Learning:**
   - The encrypted EEG images are then forwarded to a feature extraction module that utilizes transfer learning.
   - Transfer learning involves using pre-trained convolutional neural network (CNN) models to extract high-level features from the encrypted images. The models used for this purpose include ResNet50, VGG16, Xception, MobileNet, InceptionV3, DenseNet121, NASNetMobile, ResNet50V2, and VGG19. These models, which have been trained on large image datasets, can effectively capture complex features from the EEG images, aiding in more accurate seizure prediction.
4. **Seizure Prediction Using Machine Learning Models:**
   - The features extracted from the encrypted EEG images are then fed into various machine-learning models for the classification and prediction of seizures. The classification task is a binary one, where the goal is to predict whether a seizure will occur or not.

- The classification task, aimed at predicting seizures, utilizes various machine learning algorithms such as SVM, RF, GB, AB, KNN, DT, NB, and ET. These diverse algorithms collectively enhance the robustness and accuracy of seizure prediction models.

5. **Evaluation of the Methodology:**
   - The final step involves evaluating the proposed methodology under various experimental conditions to assess its effectiveness in seizure prediction.
   - The performance and safety of the method are measured using several metrics, including Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive view of the model's performance.
   - Explainable AI techniques, specifically Grad-CAM and LIME, are employed to interpret and visualize the model's decision-making process, offering insights into the critical regions of the quantum-encrypted EEG inputs that influenced the predictions.

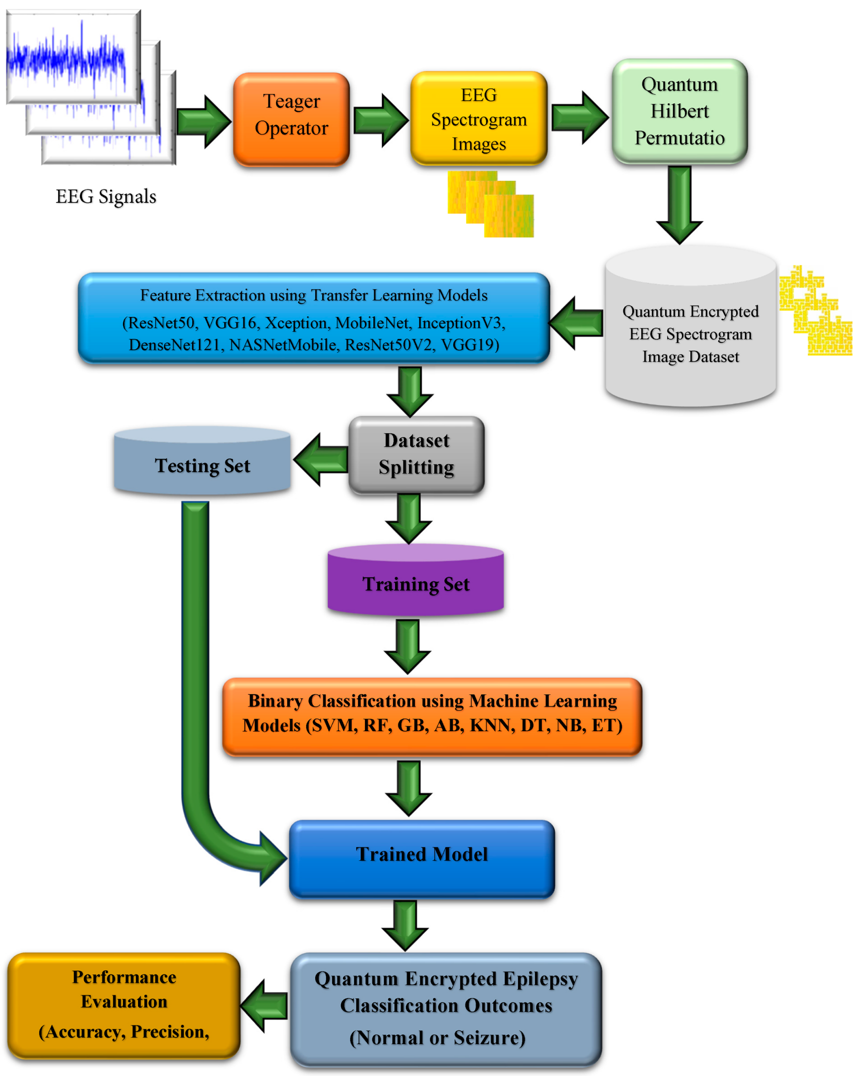


Figure 6: Comprehensive proposed hybrid deep learning system for epilepsy seizure detection in medical IoT applications.

The results are compared with existing algorithms to demonstrate the advantages and improvements offered by the proposed approach. The pseudocode for a clearly structured algorithm of the proposed technique is shown in Algorithm 1.

Algorithm 1: The Pseudo algorithm for the proposed technique on Encrypted seizure detection.

Input: EEG signals $S = \{s_K\}$, labels Y,
Output: Best trained model M^*, performance metrics

//EEG → Spectrogram Transformation
FOR each signal $s_K \in S$, DO
  $\Psi_k \leftarrow$ Teager_Energy (s_k)
  $I_k \leftarrow$ Spectrogram (Ψ_k)
  $Q_k \leftarrow$ Quantum_Hilbert_Permutation (I_k)
END
//Deep Feature Extraction (Transfer Learning)
FOR each pretrained CNN model **m** DO
  $F_m \leftarrow$ Extract_Features (**m**, **Q**)
  Split F_m and Y into Train (80%) and Test (20%)
  //Binary Seizure Classification
  FOR each classifier **c** $\in$ {SVM, RF, GB, AB, KNN, DT, NB, ET} DO
    Train model M (**m**, **c**) on Train set
    $\hat{Y} \leftarrow$ Predict on Test set
    Compute Accuracy, Precision, Recall, F1
    Store results
  END
END
$M^* \leftarrow$ Model with highest F1-score
//Explainability
Apply Grad-CAM and LIME to M^*
Compare performance with existing methods
RETURN M^*, evaluation metrics, explanation maps

5 Experimental Study

This section provides the experimental environment and the used dataset. Finally, provides the results analysis and discussion of the proposed framework.

5.1 Dataset

The CHB-MIT dataset is used for the experiments [31]. Fig. 7 displays quantum-encrypted EEG spectrogram images for normal and seizure conditions as well as samples of spectrogram images using the Teager technique. It is shown that normal signals exhibit smoother and more consistent distributions. In contrast, seizure states show irregular, high-intensity variations, highlighting abnormal neural activity enhanced through quantum-based encoding.

5.2 Evaluation Metrics

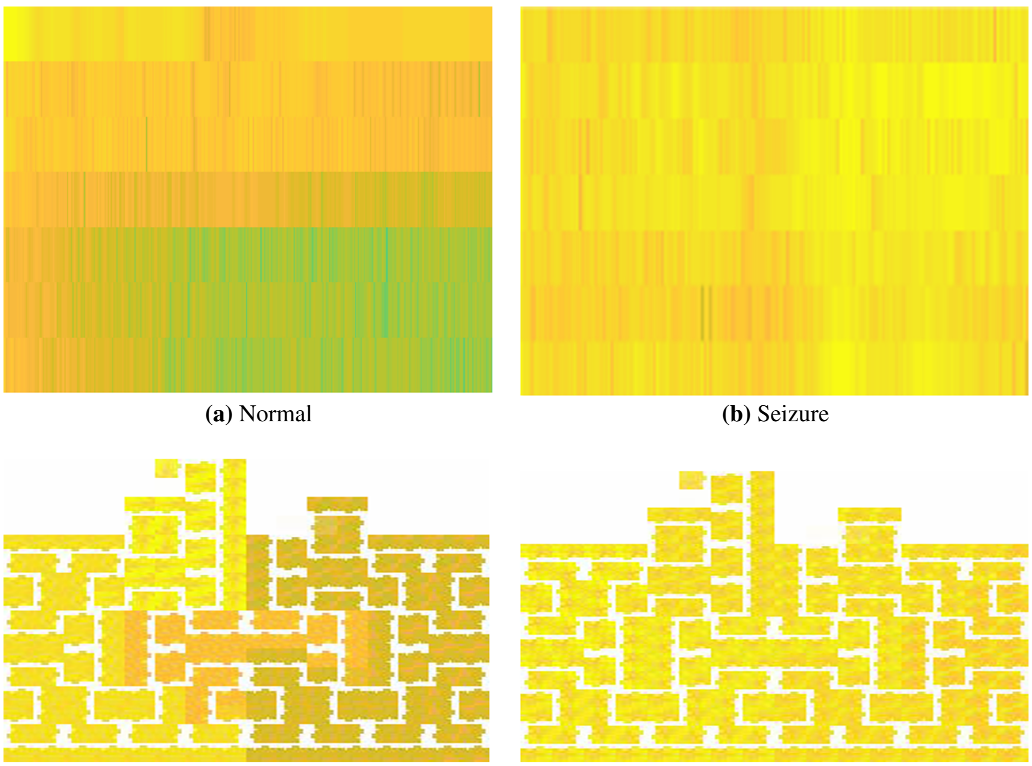
Metrics like accuracy can be used to assess how well deep learning models perform in classification and prediction tasks. After calculating the parameters in the confusion matrix, as shown in Table 1, we may compute the evaluation metrics, such as accuracy. Eqs. (7)–(10) are used to calculate the accuracy, precision, recall, and F1-score, respectively [32–35]:

$$Accuray = (TP + TN)/(TP + FP + FN + TN) \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{F1 Score} = \frac{2 * (Recall * Precision)}{\text{Recall} + \text{Precision}} \tag{10}$$



(a) Normal **(b)** Seizure

(c) Quantum_Hilbert_Normal **(d)** Quantum Hilbert_Seizure

Figure 7: Quantum-encrypted EEG spectrogram images for normal and seizure using the Hilbert algorithm.

Table 1: The parameters of the confusion matrix for seizure detection.

	Predicted Seizure	**Predicted Normal**
Actual seizure	TP	FN
Actual normal	FP	TN

5.3 Results Analysis

As we discussed, the EEG signals are transformed into 2D spectrograms using the Teager Energy Operator. The primary goal of this transformation is to capture additional texture details and features that enhance seizure prediction. After that, the EEG images were encrypted using Quantum Hilbert Permutation to produce encrypted EEG images. The encrypted EEG images are then forwarded for computerized features extraction using transfer learning as ResNet50, VGG16, Xception, MobileNet, InceptionV3, DenseNet121, NASNetMobile, ResNet50V2, and VGG19. Then, the Machine learning models are used for classifying and predicting seizures using binary classification using machine learning models such as SVM, RF, GB, AB, KNN, DT, NB, and ET al algorithms.

Finally, the proposed methodology with diverse experimental circumstances for seizure prediction through safety and performance using metrics such as confusion matrix, precision, recall, and accuracy, is compared with existing algorithms. In this section, we discuss the classification results obtained using the hybrid proposed approach. The EEG dataset was partitioned into training and testing sets using a 70/30 split for training and testing, respectively. Experiments were conducted on a system equipped with an AMD Ryzen 7 5700U CPU with Radeon Graphics, 8 GB RAM, running Windows 11, using Python.

Table 2 summarizes the performance of machine learning models using ResNet50 as a feature extractor on encrypted spectrogram images processed with the Teager method and encrypted using the quantum Hilbert encryption algorithm. SVM achieved the highest accuracy at 87.63%, with precision and recall both at 87.9% and 87.63%, respectively. RF followed closely with 86.6% accuracy and precision slightly higher at 88.61%, while recall and F1 scores were 86.6% and 86.44%. GB achieved 81.44% accuracy, with precision and recall both at 81.95% and 81.44%, respectively.

Table 2: Results of ResNet50 as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	87.63	87.9	87.63	87.61
RF	86.6	88.61	86.6	86.44
GB	81.44	81.95	81.44	81.38
AB	78.35	78.98	78.35	78.25
KNN	82.47	83.66	82.47	82.34
DT	70.1	70.2	70.1	70.08
NB	75.26	75.68	75.26	75.18
ET	83.51	84.47	83.51	83.41

Table 3 reviews the classification results using VGG16 as a feature extractor with various machine learning models on encrypted spectrogram images processed via the Teager method and encrypted using the quantum Hilbert encryption algorithm. SVM achieved the highest accuracy at 84.54%, with precision and recall both at 84.92% and 84.54%, respectively. GB also showed strong performance with an accuracy of 83.51%, precision and recall both at 83.75% and 83.51%, respectively. RF followed closely with an accuracy of 77.32%, precision of 79.86%, and recall of 77.32%, demonstrating competitive performance in classifying EEG data under encryption.

Table 4 illustrates the performance of various machine learning models using Xception as a feature extractor for seizure prediction. Random Forest (RF) achieved the highest accuracy at 85.57%, with notable precision, recall, and F1 scores. Other models like SVM, GB, and ET also performed well, with accuracies ranging from 75.26% to 83.51%.

Table 5 presents the performance metrics of various machine learning models using MobileNet as a feature extractor for seizure prediction. The Random Forest (RF) and Gradient Boosting (GB) models both achieved the highest accuracy at 81.44%, with precision, recall, and F1 scores of 82.87%, 81.44%, and 81.26%, respectively. Extra Trees (ET) also performed well with an accuracy of 80.41%, while other models like SVM, AB, and NB showed accuracies ranging from 75.26% to 79.38%.

Table 3: Results of VGG16 as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	84.54	84.92	84.54	84.5
RF	77.32	79.86	77.32	76.87
GB	83.51	83.75	83.51	83.48
AB	81.44	81.44	81.44	81.44
KNN	76.29	77.77	76.29	76.01
DT	73.2	75.38	73.2	72.67
NB	55.67	57.21	55.67	53.6
ET	80.41	82.81	80.41	80.08

Table 4: Results of Xception as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	78.35	78.98	78.35	78.25
RF	85.57	87.91	85.57	85.36
GB	83.51	84.05	83.51	83.45
AB	75.26	75.68	75.26	75.18
KNN	78.35	82.38	78.35	77.71
DT	75.26	75.68	75.26	75.18
NB	75.26	75.29	75.26	75.24
ET	79.38	81.34	79.38	79.09

Table 5: Results of MobileNet as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	76.29	76.4	76.29	76.27
RF	81.44	82.87	81.44	81.26
GB	81.44	82.87	81.44	81.26
AB	79.38	80.73	79.38	79.18
KNN	70.1	70.12	70.1	70.1
DT	70.1	70.35	70.1	70.04
NB	75.26	76	75.26	75.11
ET	80.41	82.1	80.41	80.18

Table 6 presents the evaluation metrics of machine learning models using InceptionV3 as a feature extractor on encrypted spectrogram images processed with the Teager method and encrypted using quantum Hilbert encryption. SVM achieved 80.41% accuracy, with precision and recall both at 80.76% and 80.41%. RF achieved 82.47% accuracy, with precision and recall both at 83.66% and 82.47%, respectively, demonstrating strong performance in encrypted EEG data classification

Table 6: Results of InceptionV3 as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	80.41	80.76	80.41	80.37
RF	82.47	83.66	82.47	82.34
GB	83.51	84.47	83.51	83.41
AB	82.47	85.03	82.47	82.18
KNN	73.2	75.38	73.2	72.67
DT	73.2	73.89	73.2	73.04
NB	75.26	76.43	75.26	75.02
ET	78.35	80.6	78.35	77.99

Table 7 provides machine learning model performance using DenseNet121 as a feature extractor on encrypted spectrogram images processed with the Teager method and encrypted using quantum Hilbert encryption. GB achieved the highest accuracy at 80.41%, with precision and recall both at 82.1% and 80.41%. RF also performed well with 78.35% accuracy, precision of 81.4%, and recall of 78.35%, demonstrating valuable classification of encrypted EEG data.

Table 7: Results of DenseNet121 as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	77.32	77.77	77.32	77.25
RF	78.35	81.4	78.35	77.86
GB	80.41	82.1	80.41	80.18
AB	76.29	76.88	76.29	76.18
KNN	76.29	76.6	76.29	76.24
DT	79.38	79.44	79.38	79.38
NB	64.95	66.01	64.95	64.45
ET	79.38	81.34	79.38	79.09

Table 8 summarizes the classification performed using NASNetMobile as a feature extractor on encrypted spectrogram images processed with the Teager method and encrypted using quantum Hilbert encryption. AB achieved the highest accuracy at 87.63%, precision and recall both at 87.9% and 87.63%. SVM followed with 81.44% accuracy, precision of 81.67%, and recall of 81.44%, emphasizing effective classification of encrypted EEG data.

Table 9 summarizes machine learning model performance using ResNet50V2 as a feature extractor on encrypted spectrogram images processed with the Teager method and encrypted using quantum Hilbert encryption. AB achieved the highest accuracy at 80.41%, with precision and recall both at 81.09% and 80.41%. SVM followed with 78.35% accuracy, precision of 78.68%, and recall of 78.35%, revealing efficient classification of encrypted EEG data. RF and ET also showed competitive performance with accuracies of 75.26% and 79.38%, correspondingly, showcasing robustness in processing encrypted data for seizure detection.

Table 10 presents machine learning model performance using VGG19 as a feature extractor on encrypted spectrogram images processed with the Teager method and encrypted using quantum Hilbert encryption. GB achieved the highest accuracy at 86.6%, precision, and recall both at 88.61% and 86.6%, respectively. SVM followed with 83.51% accuracy, precision of 83.75%, and recall of 83.51%, indicating robust classification of encrypted EEG data. RF also performed well with 80.41% accuracy and a precision of 83.68%, underlining valuable feature extraction and classification capabilities.

Table 8: Results of NASNetMobile as feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	81.44	81.67	81.44	81.42
RF	79.38	81.34	79.38	79.09
GB	77.32	77.53	77.32	77.29
AB	87.63	87.9	87.63	87.61
KNN	77.32	78.12	77.32	77.18
DT	70.1	70.2	70.1	70.08
NB	71.13	71.77	71.13	70.96
ET	79.38	80.73	79.38	79.18

Table 9: Results of ResNet50V2 as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	78.35	78.68	78.35	78.3
RF	75.26	76	75.26	75.11
GB	75.26	75.68	75.26	75.18
AB	80.41	81.09	80.41	80.32
KNN	73.2	73.25	73.2	73.19
DT	65.98	66.61	65.98	65.72
NB	61.86	63.84	61.86	60.25
ET	79.38	80.73	79.38	79.18

Table 10: Results of VGG19 as a feature extractor with machine learning models.

Model	Accuracy	Precision	Recall	F1 Score
SVM	83.51	83.75	83.51	83.48
RF	80.41	83.68	80.41	79.97
GB	86.6	88.61	86.6	86.44
AB	78.35	78.68	78.35	78.3
KNN	75.26	77.62	75.26	74.77
DT	75.26	76.43	75.26	75.02
NB	54.64	56.43	54.64	51.82
ET	78.35	78.98	78.35	78.25

To show the difference between all these tables and make a comprehensive comparison, Fig. 8 shows the top 15 classifiers with feature extractors of accuracy results for seizure detection. SVM achieved the highest accuracy with ResNet50 (87.63%) and VGG19 (83.51%), while RF performed well with ResNet50 (86.6%) and Xception (85.57%). Gradient Boosting showed strong performance with VGG19 (86.6%) and InceptionV3 (83.51%), highlighting effective feature extraction and classification abilities across distinctive models. However, Fig. 9 provides top 15 hybrid model of precision results for seizure detection using different machine learning models with various transfer learning models as feature extractors. RF accomplished the highest precision with SVM (88.61%) and Xception (87.91%), while GB confirmed strong performance with VGG19 (88.61%) and InceptionV3 (84.47%). SVM has proven high precision with RF (87.9%) and DenseNet121 (79.86%), demonstrating robust feature extraction and classification capabilities across diverse models.

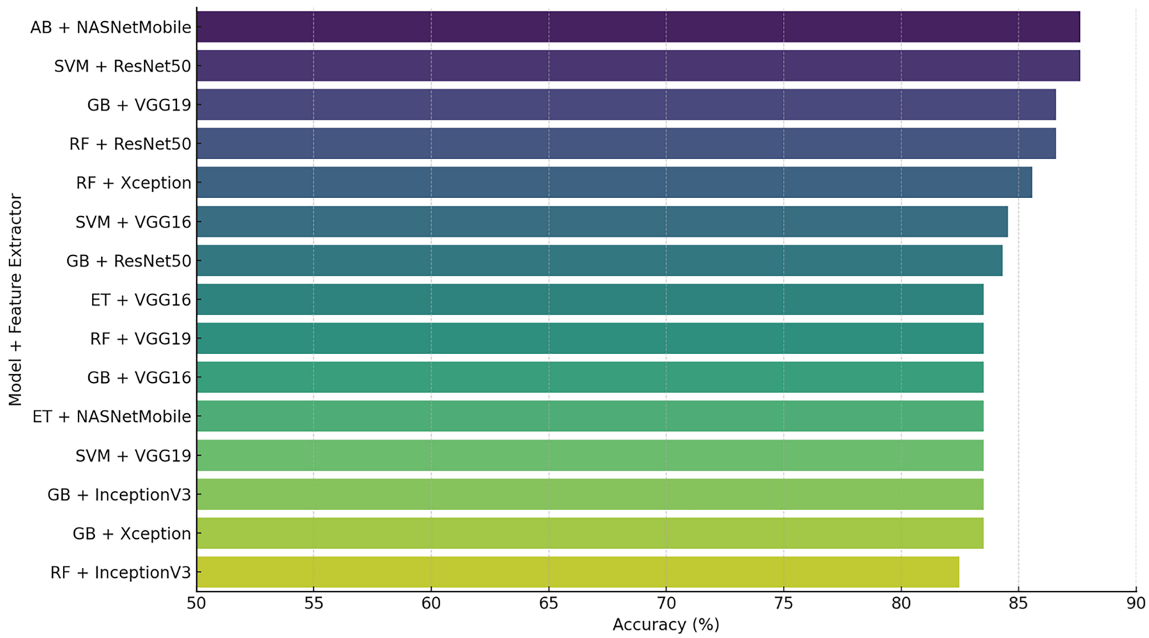


Figure 8: Top 15 classifier + feature extractor combinations of accuracy for seizure detection.

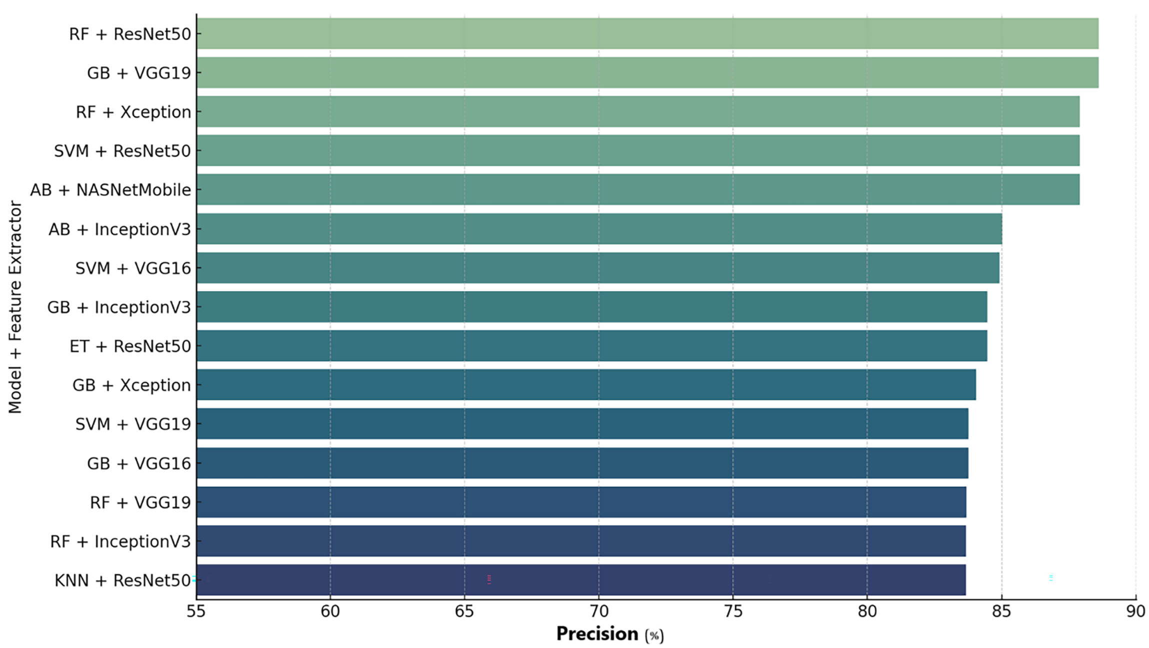


Figure 9: Top 15 classifier + feature extractor combinations of precision for seizure detection.

On the other hand, Fig. 10 shows the best recall results for seizure detection using several machine learning models with various transfer learning models as feature extractors. SVM realized the highest recall with ResNet50 (87.63%) and VGG19 (83.51%), while RF showed strong performance with Xception (85.57%) and InceptionV3 (82.47%). GB displayed the highest recall with VGG19 (86.6%) and InceptionV3 (83.51%), indicative of effective feature extraction and classification capabilities across different models. Fig. 11 shows the best recall results for seizure detection using several machine learning models with various transfer learning models as feature extractors. SVM realized the highest recall with ResNet50 (87.63%) and VGG19 (83.51%), while RF showed strong performance with Xception (85.57%) and InceptionV3 (82.47%). GB displayed the highest recall with VGG19 (86.6%) and InceptionV3 (83.51%), indicative of effective feature extraction and classification capabilities across different models.

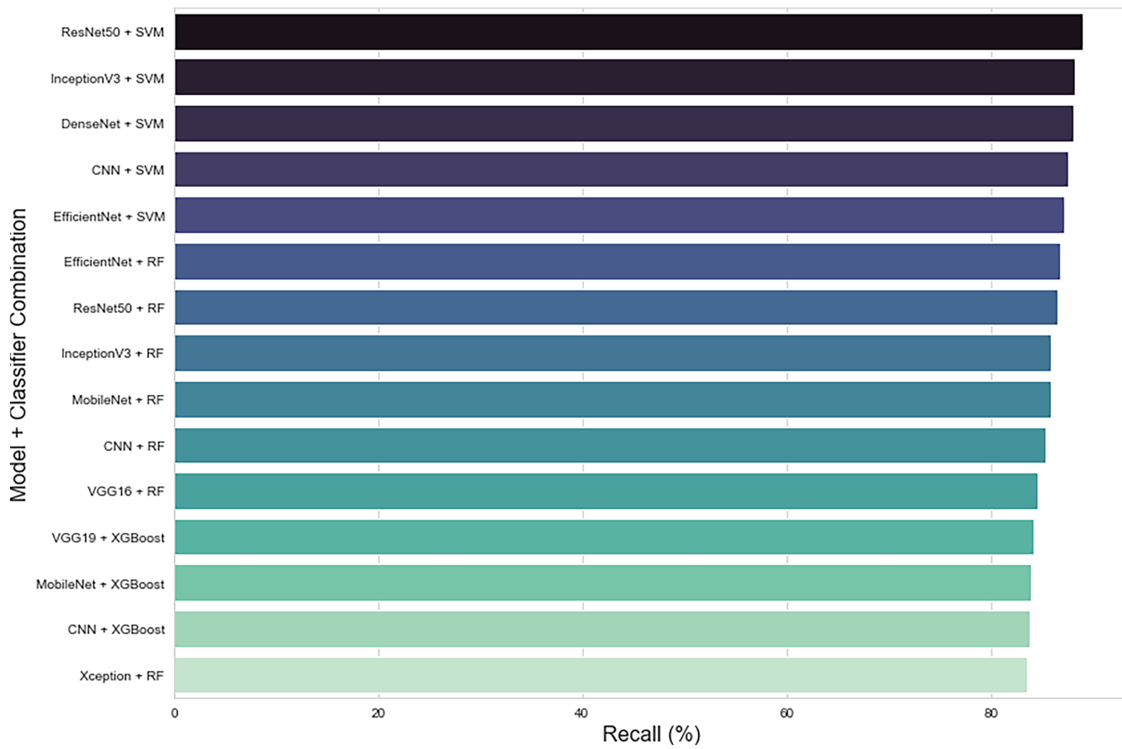


Figure 10: Top 15 classifier + feature extractor combinations of recall for seizure detection.

Fig. 11 presents the top 15 F1 score results for seizure detection using various machine learning models with different transfer learning models as feature extractors. SVM accomplished the high-ranking F1 score with ResNet50 (87.61%) and VGG19 (83.48%), Therefore, SVM with ResNet50 was identified as the overall best-performing configuration. while RF showed strong performance with Xception (85.36%) and InceptionV3 (82.34%). GB demonstrated a superior F1 score with VGG19 (86.44%) and InceptionV3 (83.41%), indicating robust feature extraction and classification capabilities across different models.

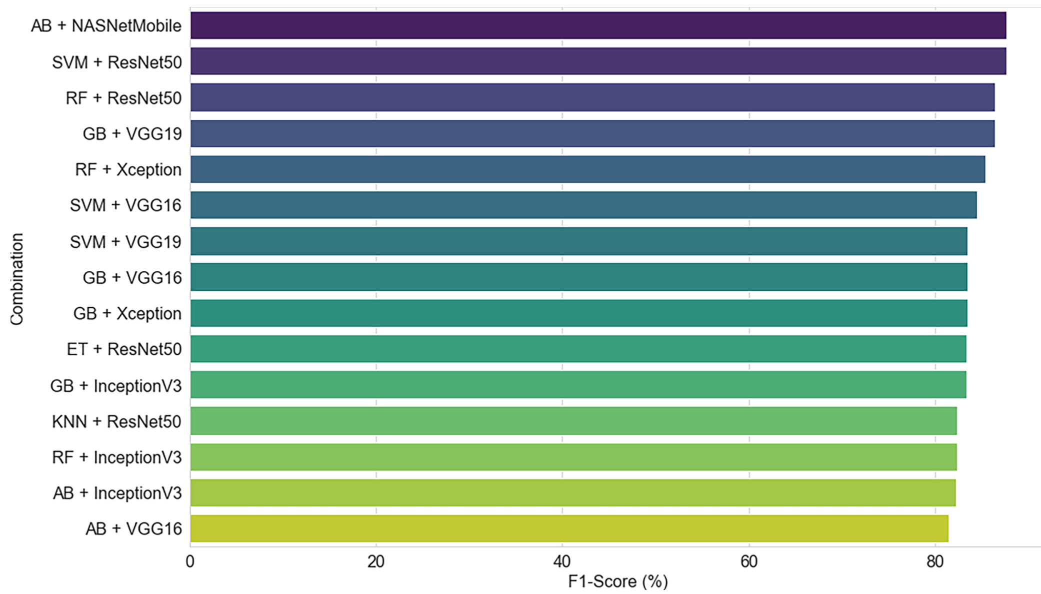
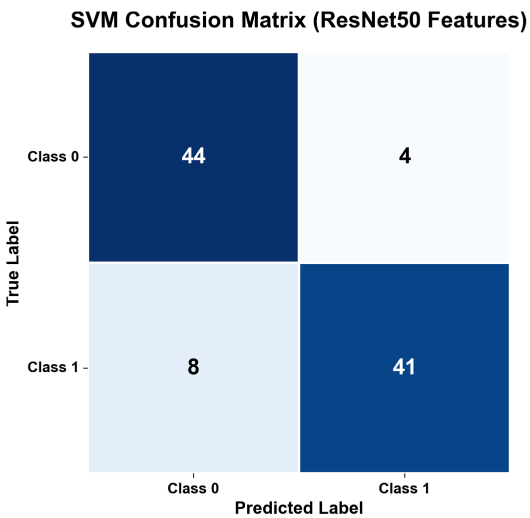


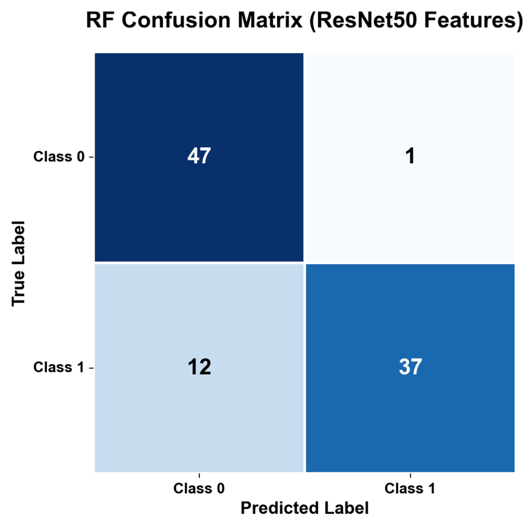
Figure 11: Top 15 classifier + feature extractor combinations of F1-score for seizure detection.

Furthermore, in Fig. 12, the confusion matrix for Resnet50 with Different Machine Learning as SVM, RF, AD, GB, and KNN. From the results above, sensitivity and specificity were computed for all models. SVM achieved 83.67% sensitivity and 91.67% specificity through the use of ResNet50 features. Random Forest provided the highest specificity (97.92%) with 75.51% sensitivity. Other models showed sensitivity between 71.43%–75.51% and specificity between 85.42%–91.67%. The results demonstrate that SVM provides optimal performance for detecting seizures while distinguishing between normal EEG patterns in clinical settings. On the other hand, ET Models and the ROC curve for Resnet50 is illustrated in Fig. 13. The ROC analysis shows that all classifiers can accurately distinguish between different classes because they use ResNet50 features, which achieve AUC values between 0.84 and 0.92. The Extra Trees algorithm reached the highest performance level with an AUC score of 0.92, while SVM and Random Forest followed closely behind with an AUC score of 0.91, which demonstrated their ability to detect seizures. In closing, the analysis of Figs. 7–10 provides valuable insights into the performance of various ML models using different TF architectures for seizure detection from encrypted EEG data. Across these Figures, the SVM consistently emerges as a strong performer in terms of accuracy, precision, recall, and F1 score metrics. SVM achieves high accuracy rates, notably with ResNet50 and VGG19, indicating classify seizure and normal EEG patterns accurately even when the data is encrypted.

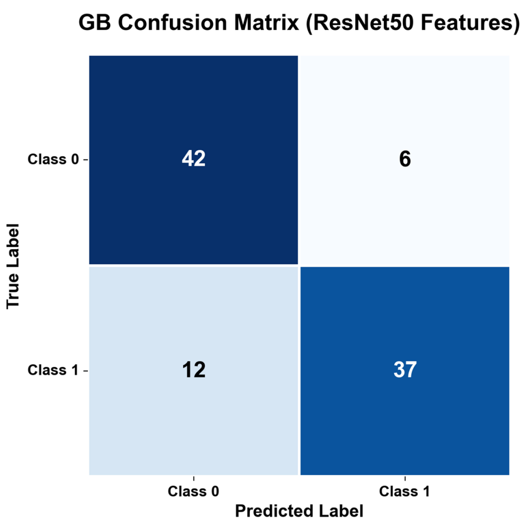
Based on the boxplot analysis illustrated in Fig. 14, it is evident that SVM and RF have tighter ranges, which reflects a consistency in their performance. This consistency is necessary to guarantee reliability and predictability of a model's outcome for the decision-makers and confidence in the generated results, reducing risks for sudden blunders in data analysis. Such is not the case with KNN and DT, which are much broader in range with performance metrics owing to their degree of variability across metric components. Also, the algorithms like GB have a permanent higher score over matrices, implying a very strong performance, but NB has the least median score coupled with the highest dispersion, implying that it is being employed around herein, ill-suited. So, the GB's higher scores make it attractive for cases in which overall performance counts since such strength comes at a cost of computational resources. Further, in contrast, performance variability and lower median scores of NB indicate its possible unreliability in this regard and thus considerable caution or extra tuning should be applied if adopted.



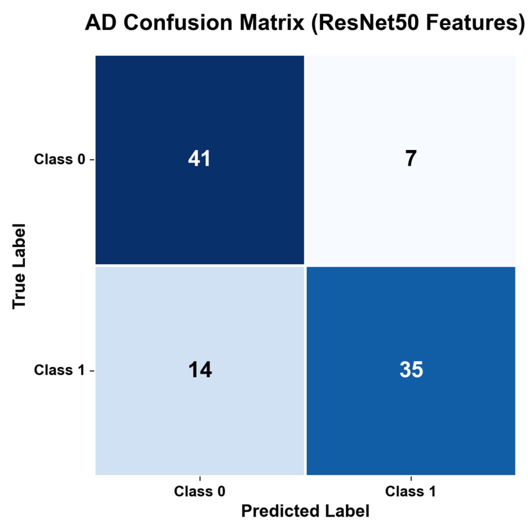
(a) SVM



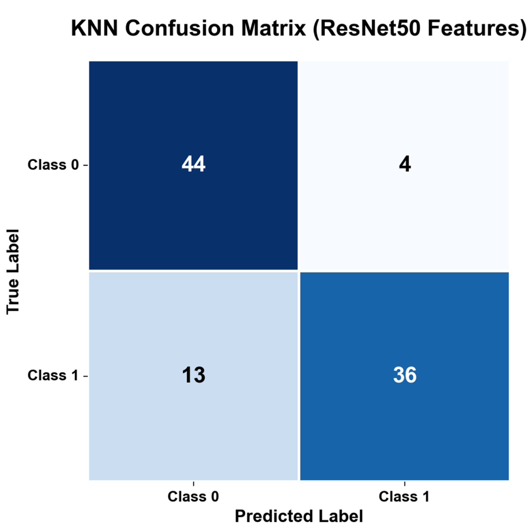
(b) Random Forest



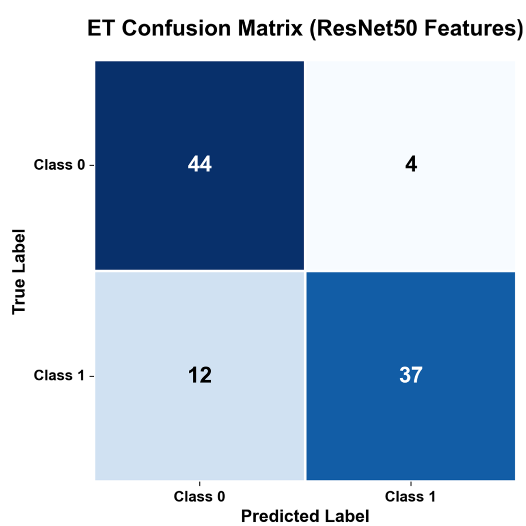
(c) Gradient Boost



(d) AdaBoost

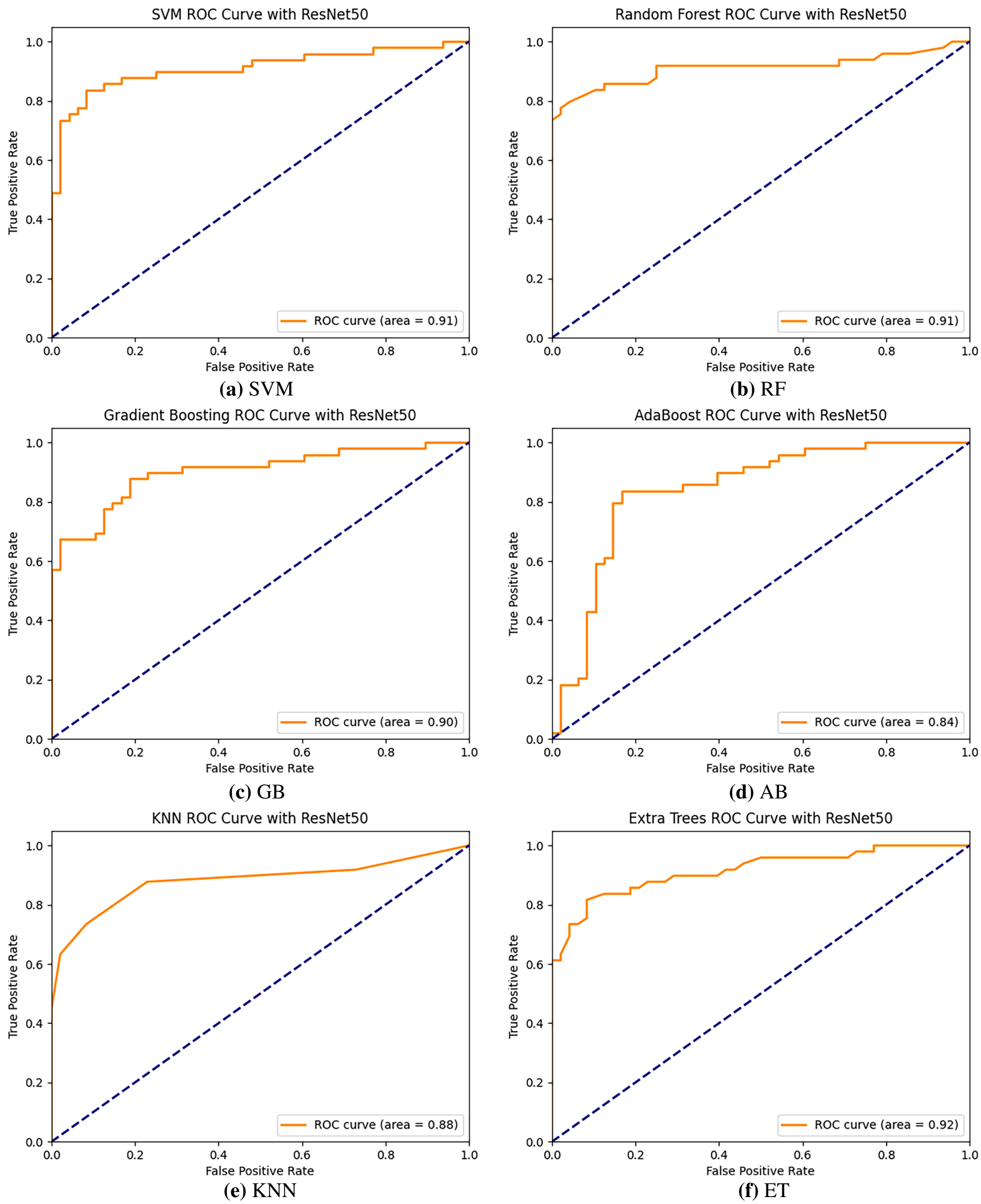


(e) KNN



(f) Extra Tree

Figure 12: Confusion matrix for ResNet50 with different machine learning models.



(a) SVM **(b)** RF **(c)** GB **(d)** AB **(e)** KNN **(f)** ET

Figure 13: ROC curve for ResNet50 with all machine learning models.

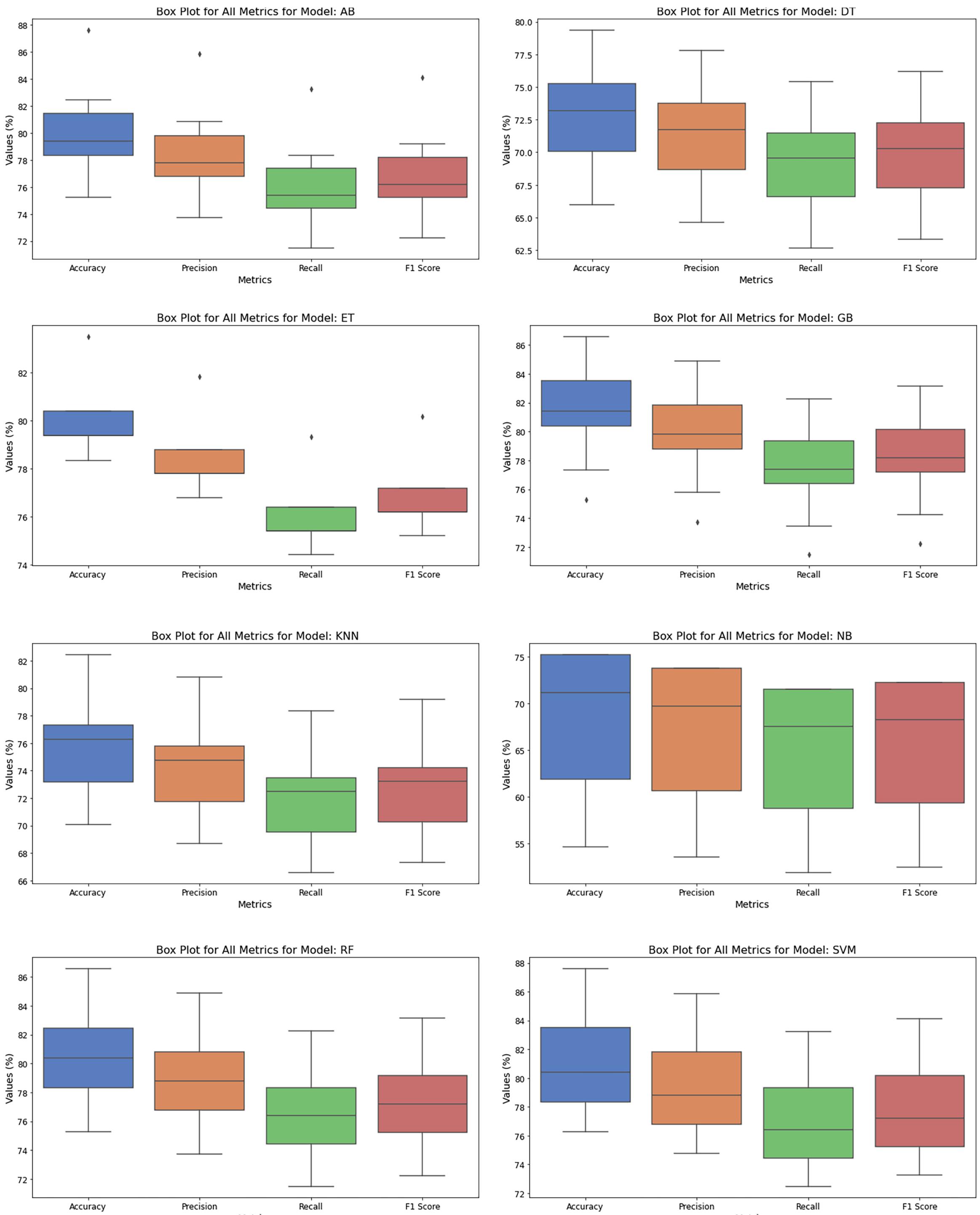


Figure 14: Box plot for all machine learning models.

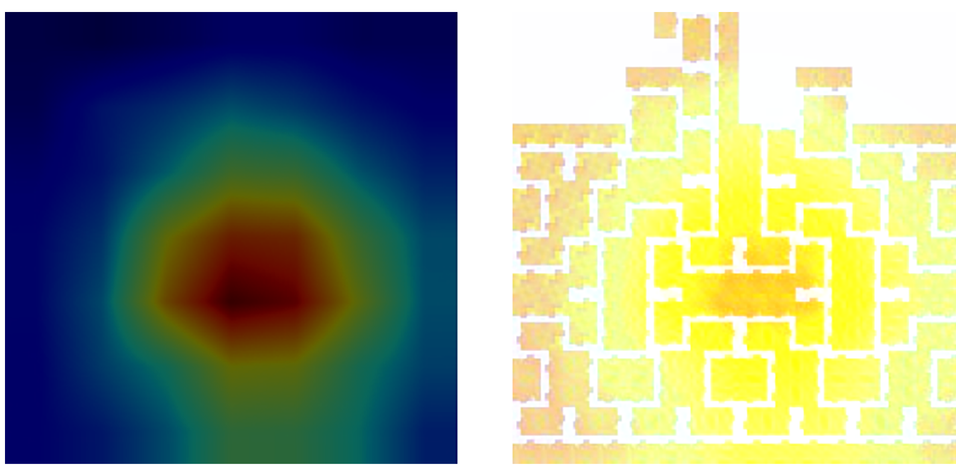
This underscores SVM's effectiveness in leveraging the extracted features from deep transfer learning models to discern subtle differences in EEG signals associated with seizures. Additionally, RF demonstrates competitive performance, particularly excelling in precision metrics when paired with models like SVM and Xception. RF's ability to maintain high precision while achieving notable recall rates reflects its suitability for applications where minimizing false positives is crucial. Moreover, GB and other models show consistent performance across different metrics, demonstrating their utility in seizure detection tasks.

Generally these results indicate that application of advanced transfer learning techniques such as ResNet50, VGG19, and Xception under the umbrella of powerful machine learning algorithms like SVM and RF indicates a mark making towards the improvement of accuracy and reliability of seizure detection systems even while handling encrypted EEG data in sensitive medical contexts, this may considerably impact healthcare with a veritable potential for improved patient outcomes through rapid and accurate seizure detection, and extending the technology to other medical applications such as vital signs monitoring and diagnostics.

5.4 Explainable AI

This section illustrates the explainable AI for the figure using Grad-CAM and LIME to evaluate the results for the classification of the encrypted image, as shown in Figs. 15–17. The graphs provide an exhaustive interpretability analysis of a quantum-encrypted EEG image for seizure detection. The Original Image pertains to the encrypted representation of the EEG signal converted into a structured visual format. Owing to encryption, the raw signal features are unrecognizable to a human; therefore, XAI methods such as GRAD-CAM and LIME were considered post-classification as a means of interpreting the hybrid learning model's predictions. These methods help to understand which portions of the encrypted input affect the decision of the model the most, without going to the base EEG signal in the process.

The GRAD-CAM output, as shown in Fig. 14, highlights the portions of the encrypted EEG image that strongly influenced the deep learning model's predictions. In the heatmap, red and yellow areas denote high activations that imply such regions contain encoded patterns heralding seizure activity. The Grad-CAM Overlay takes this a step further by fusing the heatmap and original image together to aid in the spatial alignment between the encrypted structure and the localized focus areas of the network. These visuals demonstrate that the model has indeed picked up on seizure-specific cues even through these largely quantum-obfuscated image domains, thereby attesting to its robustness and attention mechanisms.



(a) (b)

Figure 15: The GRAD-CAM output: (**a**) GRAD CAM; (**b**) GRAD-overlay Encrypted image.

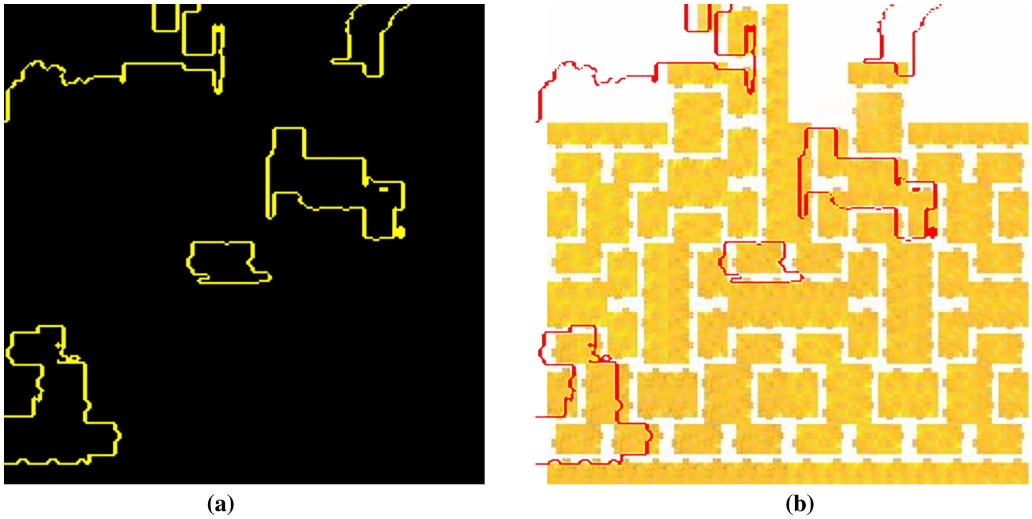


Figure 16: The LIME output: (**a**) LIME results; (**b**) LIME-overlay encrypted image.

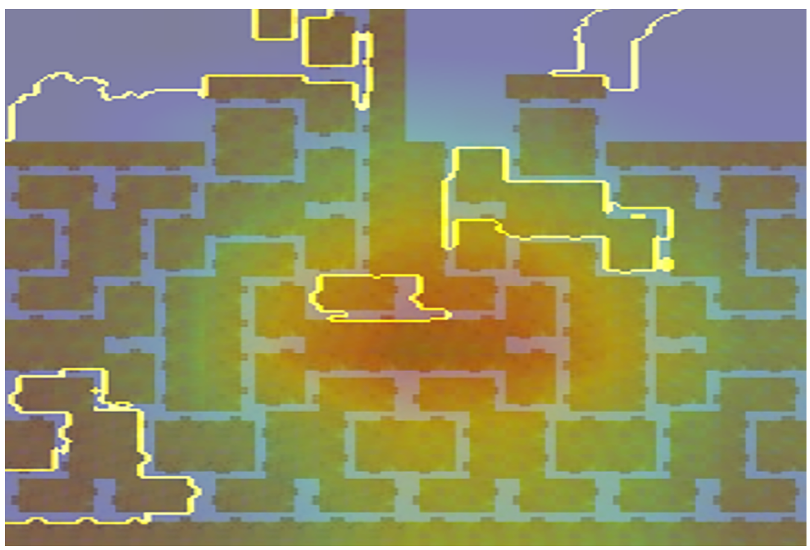


Figure 17: The combined overlay of XAI.

The LIME graph Fig. 15, on the contrary, will give a complementary view, displaying areas (red, for clarity) deemed most relevant to the class decision via local perturbations of an input. The GRAD-CAM permits a global explanation, whereas LIME makes available a feature importance map specific to a locality. This dichotomy allows one to really look at the broader decision maker as well as some finer grains of sensitivity of the model. Most importantly, the areas in red as highlighted by LIME also correspond with the major spatial zones preferentially marked by GRAD-CAM, which further supports the presence of a reliable and consistent model interpretation framework.

The Combined Overlay in Fig. 16 blends the two outputs, showing in which regions they agree. This intersection lends weight to the interpretability of the classification decision and shows that the model is, indeed, focused on discriminative regions in the encrypted representation. The background represents the encrypted EEG feature map extracted from the deep learning model, while the overlaid heatmap (from blue to red) indicates the regions contributing most to the seizure prediction—where red/yellow zones denote high model attention and blue regions indicate low influence. The yellow boundary outlines the detected activation zones, showing strong agreement between Grad-CAM and segmentation results, confirming that the model's focus aligns with clinically relevant seizure patterns. The XAI maps created in this work were not based on EEG images, but their function was to ensure that the suggested Quantum Hilbert Encryption keeps the spatial discriminative to the model detectable patterns. This confirms that encryption does not hide the features that are important for diagnosis. Nevertheless, the clinical interpretability needs to be based on decrypted representations or raw spectrograms.

5.5 Comparative Study

Table 11 compares the proposed system with existing approaches in seizure detection from EEG data. The existing methods include a CNN model applied to the CHB-MIT dataset, achieving an average F1-score of 69.34% in [36]. However, the Time, Freq., Graph with SVM achievied an accuracy and recall of 85.75% in [37], and Deep Metric Learning, which achieved 86.68% accuracy on the CHB-MIT dataset [38]. Another study using Googlenet on encrypted EEG data reports accuracies ranging from 84.21% to 88.89% with different encryption methods [39]. In contrast, the proposed system employing Transfer Learning with Machine Learning on encrypted EEG data processed with Quantum Hilbert achieves SVM accuracies of 87.63% (ResNet50) and 83.51% (VGG19), and RF achieves high precision scores of 88.61% (SVM with ResNet50) and 87.91% (RF with Xception). These results highlight the competitive performance of the proposed system in accurately detecting seizures from encrypted EEG data compared to existing methodologies.

Table 11: A comparative study between the proposed system and existing work.

Work	Models	Dataset	Results
[36]	CNN model	CHB-MIT	Average F1-score of 69.34%
[37]	Time, Freq., Graph with SVM	CHB-MIT	Accuracy of 85.75% and recall of 85.75%
[38]	Deep Metric Learning	CHB-MIT	Accuracy of 86.68%
[39]	Googlenet	Encrypted EEG using Arnold and Chaotic	86.11%, 84.21%, and 88.89% for Arnold while 84.72%, 82.05%, and 88.89% for chaotic
Proposed system	Transfer Learning (TL) with ML and XAI	Encrypted EEG with Quantum Hilbert	The SVM achieves top accuracy with scores like 87.63% (ResNet50) and 83.51% (VGG19), while RF excels in precision with results such as 88.61% (SVM with ResNet50) and 87.91% (RF with Xception)

6 High-Level IoT-Based Privacy-Preserving Seizure Detection System

Effectively delivering a more dependable and practical smart medical system, this framework enhances healthcare efficiency. The proposed framework consists of three crucial phases, each with distinct tasks and procedures that work together to achieve system goals, as illustrated in Fig. 18:

1. Phase 1: Real-time encrypted EEG data collection and capture efficiently using smart medical IoT devices.
2. Phase 2: Submission of the collected EEG data to cloud servers for processing and storage. This phase organizes user data from internet-connected smart devices, making it accessible for medical examinations. Cloud-based data analysis and preprocessing are also employed to identify potential disorders.
3. Phase 3: Medical staff uses a cloud-based dashboard tracking system to monitor patient epilepsy statistics. The system generates reports through cloud-based AI predictions, allowing staff to review and determine the appropriate seizure detection measures.

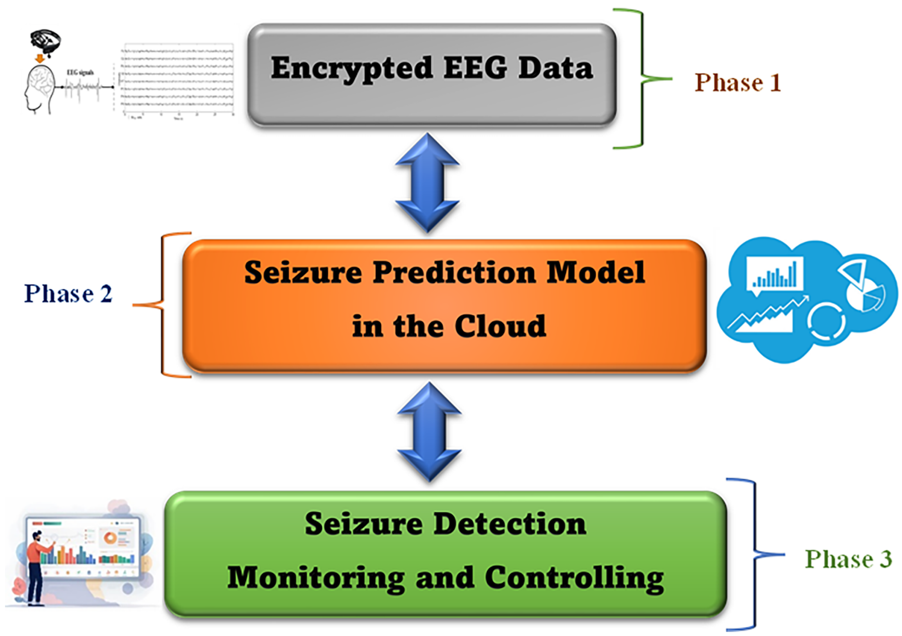


Figure 18: Proposed smart monitoring framework for initial seizure prediction.

7 Conclusion and Future Work

This study presents a secure and efficient seizure detection on encrypted EEG images using the quantum Hilbert algorithm and a hybrid deep learning model. In this work, the EEG signals are transformed into 2D spectrograms using the Teager Energy Operator to enhance seizure prediction and then encrypted using Quantum Hilbert Permutation. These encrypted images are processed with transfer learning models (e.g., ResNet50, VGG16) for feature extraction, followed by seizure prediction using various machine learning algorithms (e.g., SVM, RF). The methodology is evaluated under different conditions using metrics like precision, recall, and accuracy, and compared with existing algorithms. The results indicate that the SVM demonstrates superior accuracy, achieving scores of 87.63% with ResNet50 and 83.51% with VGG19. In contrast, RF stands out in terms of precision, with impressive scores such as 88.61% for SVM with ResNet50 and 87.91% for RF with Xception. These findings confirm the effectiveness of both methods in detecting seizures using encrypted EEG data. Finally, the proposed system can assist and empower doctors worldwide in securely diagnosing seizures at an early stage in an effective manner.

Nevertheless, the present framework suffers from computational overhead during the quantum encryption and deep feature-extraction processes, which may limit the real-time deployment of this method as well as scaling up in resource-constrained situations. Quantum encryption, although a powerful tool for protecting the transmission of sensitive data, secure data transmission protocols, access control mechanisms, and compliance with healthcare privacy standards remain essential for practical implementation. In the Future plan, we will focus on enhancing security through advanced quantum encryption techniques and validating the system on larger, more diverse datasets. Furthermore, real-time implementation and integration of multimodal data will be explored to enhance seizure detection accuracy and robustness. Ultimately, developing user-friendly interfaces and conducting extensive clinical trials will facilitate the adoption of this technology in real-world healthcare settings. Future work will include quantitative XAI metrics (e.g., deletion/insertion and sanity checks) to confirm interpretability in both encrypted and decrypted domains.

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Availability of Data and Materials: The data that support the findings of this study are openly available in CHB-MIT dataset at https://physionet.org/content/chbmit/1.0.0/.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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