Screening Epileptic Seizures in EEGs Using Interictal Epileptiform Discharge Waveforms and Convolutional Neural Networks

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Abstract

The integration of Artificial Intelligence (AI) within the Medical Internet of Things (MIoT) is advancing swiftly, leading to significant developments in the detection of illnesses like epilepsy by analyzing Interictal Epileptiform Discharges (IED) in electroencephalograms (EEG).The availability of EEG data has facilitated the creation of innovative applications, including seizure detection. While neurologists have traditionally relied on EEG data analysis to identify epileptic seizures, the manual evaluation of EEG brain waves is a laborious and complex process that places significant stress on specialists. This paper presents a simple Convolutional Neural Network (CNN) method for the automated detection of IEDs based on EEG waveforms. This approach helps reduce the burden on epilepsy patients by forecasting seizures and enabling timely interventions. It also eases the workload for neurologists and less experienced specialists, thereby accelerating the diagnosis process. The proposed method was implemented by utilizing a series of images that depicted the magnitude of the EEG signal across each sensor. The study divided participants into two groups: (A) healthy individuals and (B) individuals with epilepsy. The results demonstrated an accuracy of up to 96.4% compared to human expert diagnoses, displaying the method's effectiveness and practicality in detecting seizure occurrences in EEG data.

Keywords: Interictal epileptiform discharge; Electroencephalogram; Convolutional neural network; Epilepsy; Seizure detection

1. Introduction

As the center of all cognitive and sensory inputs, the brain as well oversees the body's vital activities. It generates sophisticated and complex bio potential signals while accomplishing these processes [1]. These signals can be captured in a variety of ways. These recordings, known as electroencephalograms (EEG), give a wealth of information about the functioning of the brain as well as other organs of the body [2]. Previous researches have employed EEG signals because they are inexpensive and provide a lot of information. Furthermore, aberrant activity of these signals is employed for illness identification and offers significant information for disease monitoring [3]. Epilepsy is one of these illnesses that may be recognized by EEG readings [4]. This condition is believed to affect around 70 million individuals worldwide, with 2 to 4 million new cases identified each year [5]. Epilepsy is a central nervous system condition characterized by aberrant brain activity, which can cause seizures, unusual behavior and sensations, and, in rare cases, loss of consciousness [6].Seizures and Interictal Epileptiform Discharge (IEDs) are regarded two forms of epileptic brain processes [7]. IEDs have fast become one of the most important components of epilepsy diagnosis, and they may be used to locate epileptic foci, which manifest as acute spikes and waves [8]. From a clinical standpoint, IEDs are frequently evaluated by specialists utilizing EEG visual analysis, which has long been regarded the gold standard. However, eye inspection is time-consuming and subjective, resulting in up to 30% misdiagnosis [9].

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Artificial intelligence (AI) is critical in telemedicine applications for treatment planning, personalized diagnosis, and sickness management [10]. Furthermore, despite the immense complexity of EEG data, machine learning has just revolutionized seizure detection. It has also aided in the identification and evaluation of seizure features [11, 12]. In 1976, the first computer-assisted IED detection equipment was developed by establishing a scalp EEG-based algorithm to automatically identify IEDs. As a result, much research on autonomous IED detection systems, spanning from simulated methods to deep learning techniques, has been done [13]. As a result, until recently, machine learning was frequently utilized in epilepsy detection and seizure prediction [14]. Recently, while research has mostly focused on deep learning algorithms that excel in disciplines like computer vision and speech recognition [15]. Machine learning has the ability to greatly decrease the cost and time of epileptic seizure and EEG signal processing, and decrease the strain on doctors, while improving diagnostic efficiency [16].

Some students in educational institutions are prone to have epilepsy, and they are afraid of having epileptic seizures in front of their peers. As a result, the primary focus of our research is on the accurate identification of seizure occurrences in EEG picture recordings. Manual examination of EEG brain waves for epilepsy identification is also a time-consuming and demanding operation that puts neurologists under a lot of stress. Therefore, this work proposes a machine learning-based method for categorizing EEG images into seizure and non-seizure episodes, as well as detecting the existence of seizure episodes in EEG data. The technique was evaluated using Mansoura University Hospital's EEG dataset.

The suggested system considerably reduces the dimensionality of the data. Furthermore, it has the ability to reduce the considerable clinical workload of neurologists in the medical system. It also assists medical students and less experienced clinicians in reading EEGs, hence shortening diagnostic time. The following are the significant contributions made in this study:

- Presenting a pre-processed EEG dataset from Mansoura University Hospital.
- Investigating the use of custom vision AI for dataset creation.
- Advising smart telemedicine systems on an effective and secure IoT-based epilepsy detection and diagnostic solution.
- Developing a novel framework for lowering the dimensionality of EEG waveform representation using tensor decomposition and feeding the reduced data to a CNN to improve model efficiency and minimize training complexity.
- Investigating and testing the suggested system in terms of accuracy. Investigating and testing the suggested system in terms of accuracy. We used accuracy, recall, precision and the confusion matrix associated with current algorithms to estimate performance.

The rest of this work is organized as follows. The second section presents an overview of existing relevant work utilizing EEG data for seizure detection. The third part discusses the proposed system, including the dataset, and explains the CNN module that is employed. Section 4 presents the application and experimental findings. Finally, in Section 5, the findings are presented.

2. Related Work

It is difficult to distinguish between epileptic and non-epileptic EEG readings. It requires obtaining and identifying discriminating factors from an EEG wave pattern. In this part, we will present an overview of the associated cutting-edge ways for classifying epileptic and non-epileptic EEG wave patterns using various feature extraction and classification algorithms. Athar A. Ein Shoka et.al an innovative and efficient encrypted EEG data classification and recognition system was presented by combining chaotic baker map and Arnold transform algorithms with CNNs. The channel's EEG time series was first converted into a 2D spectrogram image, then encrypted using chaotic baker map and Arnold transform algorithms, and then fed into CNNs-based Transfer Learning (TL) models. Using Googlenet and the Arnold and chaotic approaches, the suggested structure's accuracy was determined to be up to 86.11% and 84.72%, respectively. [17]. Neethu Sreenivasan et al. introduced a detection system that combines manual and automated methods using seizure feature amplification analysis, aimed at reducing practical challenges. Their algorithm, inspired by telecommunications principles, treats seizures as carriers of information and optimizes filters accordingly, providing a cost-effective computational solution. Manual tests demonstrated 93% sensitivity and 96% specificity. Automated analyses achieved 88% sensitivity and 97% specificity. Additionally, their proposed method accurately identifies seizure locations within the brain [18]. Syed Yaseen Shah et al. utilized a recent EEG dataset to apply advanced deep learning algorithms, including random neural network (RNN), convolutional neural network (CNN), extremely random tree (ERT), and residual neural network (ResNet), to classify various types of epileptic seizures from non-seizures. Their findings indicated that RNN exhibited superior performance compared to other algorithms, achieving an initial accuracy of 97%, which slightly improved following cross-validation. [19]. Fatima Hassan et.al recommended combining

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Convolution Neural Networks (CNN) with machine learning classifiers. The Butterworth filter was used to preprocess the EEG data, and then CNN was employed to extract features. The technique relied on mutual information-based estimators to choose just the relevant features from the extracted set of data, so alleviating the curse of dimensionality and boosting classification accuracy. For CHB-MIT datasets, their model accurately predicts 98% of the time [20]. Anwer Mustafa Hilal et al. introduced an advanced epileptic seizure detection and classification model, termed DCSAE-ESDC, leveraging intelligent deep canonical sparse auto encoder technology applied to EEG signals. The methodology had focused on two primary phases: feature selection and classification. Parameter optimization of the DCSAE model was achieved through the krill herd algorithm (KHA). Comparative analysis demonstrated superior performance of the DCSAE-ESDC technique compared to existing methods, achieving peak accuracies of 98.67% and 98.73% in binary and multi-class classifications [21]. Afef Saidi et.al proposed combining CNN's learning capacity and SVM classifier's generalization ability. As a result, CNN was used for feature extraction to reduce feature engineering, while SVM was used for seizure detection (epileptic/normal). Using scalp EEG data, the suggested combined CNN-SVM model was verified. The suggested technique outperformed the baseline CNN model in terms of accuracy [22]. Rabel Guharoy et.al Discrete Wavelet Transforms (DWT) and machine learning classifiers were used to identify epilepsy. In this scenario, DWT was used to extract features. Principal Component Analysis (PCA) was then applied to separate sub-bands. The EEG data was classified using the Support Vector Machine (SVM) classifier, the K-Nearest-Neighbor (KNN) classifier, and the Naive Bayes (NB) classifier. On Bonn datasets, the proposed approaches reach a maximum recognition accuracy of 100% for KNN, SVM, and NB classifiers [23]. Deepa B and Ramesh K utilized the renowned CHB-MIT scalp EEG database to develop a pre-processed dataset. They applied the Bidirectional Long Short Term Memory (BiLSTM) algorithm, with Min Max Scaler normalization, to train and test a deep learning model on this dataset. The results are highly promising, demonstrating an accuracy of 99.55% for the proposed model when evaluating seizure activity data across all patients [24]. Bassem Bouaziz et.al illustrated how CNN may be used to categories EEG images in a thorough and trustworthy manner. The proposed method was applied to images that represented the amplitude of the EEG data across all electrodes. There are two groups being studied: (a) healthy individuals and (b) epileptic people. The classification results indicated that CNN can categories EEG data and detect epileptic seizures with 99.48% accuracy [25].

According to the above-mentioned evaluation of the most recent studies, the bulk of feature extraction algorithms are handcrafted and not data-adapted to the data. Deep Learning (DL) may be used to improve an epilepsy detection system's accuracy and generalization. To the best of our knowledge, DL techniques for epilepsy diagnosis have not been routinely used. This might be due to a lack of accessible data, which would be insufficient to train a deep model. As a result, we were inspired to use deep learning to develop a deep model with a minimal number of learnable parameters that efficiently identifies EEG brain signals as epileptic or not.

3. Proposed System

The first goal of the study is to detect epileptic seizures from EEG waves by extracting characteristics. Following feature extraction, the CNN classifier is utilized to categories various types of EEG wave patterns. Figure 1 depicts the generic classifier design.

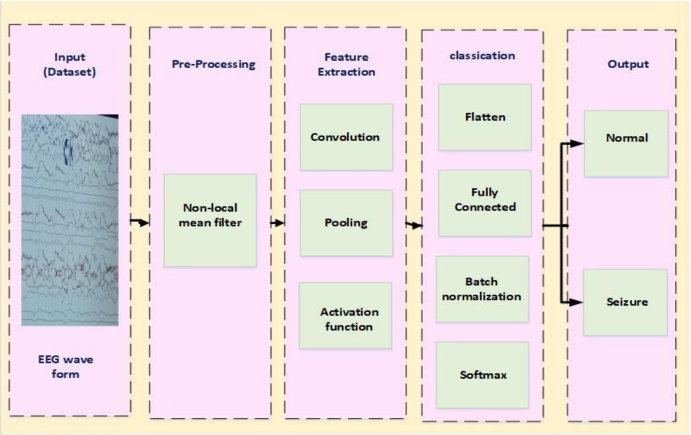

Figure 1. General System Architecture

The suggested system's implementation included many phases, which are explained in the following subsections.

3.1 Dataset

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In this work, we use an EEG dataset from Mansoura University Hospital that was gathered from patients (both male and female) between 2022 and 2023. The information was separated into two groups, set (A) and set (B). EEG recordings of set (A) recorded in conscious mental state with open and closed eyes from the healthy patient's head surface. The set (B) is obtained from epileptic patients (PwE) and is taken throughout the seizure free period as well as during the epileptic event. Figure 2 displays EEG waveform samples for sets (A & B). The dataset model was constructed using Microsoft Azure's custom vision AI application.

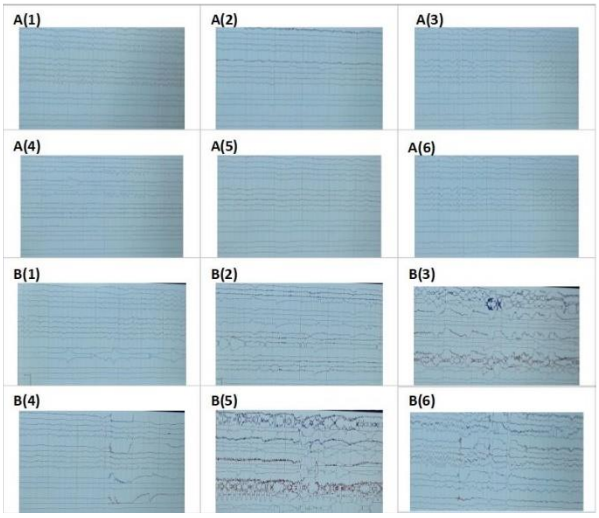

Figure 2. Samples of EEG wave form for sets (A & B)

3.2 Pre-processing

Pre-processing is used to minimize noise from the EEG waveform so that the characteristics and findings are more accurate. As a result, we concentrated on picture preparation techniques such image denoising. As a result, we choose a common denoising approach and place it before the convolutional neural network module. This phase employs a Non-local mean filter, which employs all of the pixels in the picture and weights them according to some form of similarity. The picture clarity is good after filtering, and the details are not lost, so the image's structural information is better safeguarded. If the noisy image v (i) is defined as the sum of the picture u (i) and the noise n (i) with a mean value of 0 and no noise contamination, v (i) may be represented as:

$$V(i) = u(i) + n(i) \tag{1}$$

Assuming that the denoised picture is I(i), the NLM computation is as follows for a pixel i, the image block N(i) with i as the block center, and N(j) is an image block in the neighborhood of N(i). [26, 27] :

$$I\ (i) = \frac{\sum W(i,j)v(j)}{\sum w(i,j)} \tag{2}$$

3.3 Feature Extraction

The purpose of the feature extraction step is to convert raw data into numerical features that can be processed while retaining the original data set's content. It also reduces the amount of features in a dataset. It outperforms just applying machine learning to raw data. It is also the stage at which the network learns to recognize a number of high-level features in the input images. It is composed of convolution and pooling layers. Figure 3 depicts the feature extraction steps.

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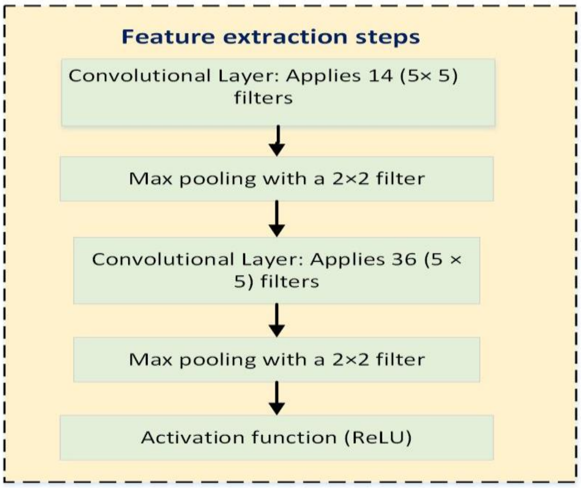

Figure 3. Feature Extraction Steps

3.3.1 A convolutional Layer: This layer consists of convolutional kernels, with each neuron serving as a kernel. However, if the kernel is symmetric, the convolution process will be a correlation process. The original image has been split into separate sections known as receptive fields by the convolutional kernel. This division technique facilitates in the extraction of features. Kernel convolves with the images by multiplying the appropriate elements by the receptive field's multiplying elements with a given set of weights. To estimate the convolution process, use the following equation [17, 28]:

$$f_l^k(p,q) = \sum_{c} \sum_{x,y} i_c\,(x,y).\,e_l^k(u,v) \qquad (3)$$

where f_l^k is the output of the convolutional layer. CNN parameters are more efficient than fully connected networks since they are obtained by sliding a kernel with the same set of weights across an image. Convolution operations are further classified according on the kind and size of filters used the type of padding used, and the direction of convolution. In this case, we apply n filters on the EEG wave pattern. We also use 14 and 36 filters with kernel sizes of 55 and the same padding. Finally, the Relu activation function is used. The size of the output will be [28, 28, 14].

3.3.2 Pooling Computation: The pooling computation comes after the convolution process. The convolution procedure generates Feature motifs, which may exist in various positions throughout the image. The main aim is to gradually minimize the number of parameters and calculations. As a result, it is often referred to as down-sampling. The pooling layer's functioning is regulated by the equation below [17, 29]:

$$Z_l^k = g_p(f_l^k) \qquad (4)$$

Where Z_l^k is the pooled feature-map of layers for the input feature-map. It will lower the data's dimensionality. We utilize the max pooling module with a size of 22 and stride of 2. As input, we utilize the preceding layer. The size of the output will be [batch size, 14, 14, 14].

3.3.3 Activation Function: The activation function introduces nonlinear variables to minimize redundant input while preserving features; it retains the "active neuron feature" and maps out these features with nonlinear functions, which is essential for the neural network to tackle the tough nonlinear problem. [30] We adopted the rectified linear unit function (ReLU) in our system because of its efficient features in neural networks. The ReLU function is defined as follows [31]:

$$f(x) = \max(0, x) \qquad (5)$$

Where x is the activation function's input, which is an output of a convolution.

3.4 Classification:

The final stage is to classify the EEG waveform once the characteristics have been extracted. Convolution and pooling layers' extracted features are now given to fully linked layers. The following is a quick description of the classifiers used for classification. Proposed method is demonstrated in Figure 4.

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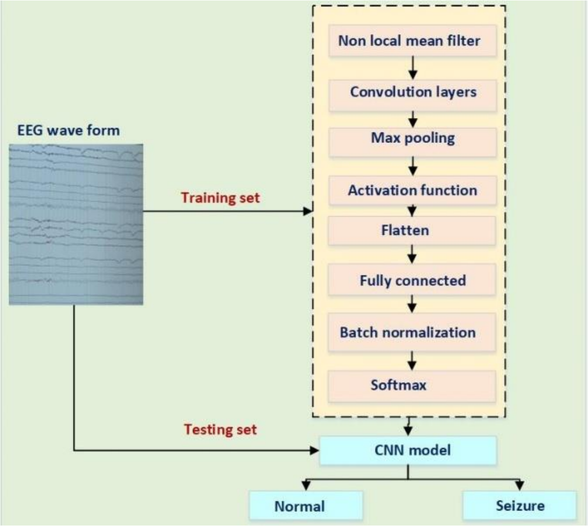

Figure 4. The proposed CNN classification

3.4.1 Batch Normalization (BN) is a well-known approach for expediting deep network training by incorporating data standardization within the network design [32]. A BN layer requires the mean and variance of input components per channel to be assessed throughout the full mini-batch dataset [33].

3.4.2 Flattening layer after completing the preceding two processes, we get a pooled feature map. Flattening is used to combine all of the 2-Dimensional arrays produced by pooled feature EEG pictures into a single long continuous linear vector [34].

3.4.3 Fully Connected Layer (also known as Hidden Layer) is the convolutional neural network's last layer. This layer is made up of an affine function and a non-linear function. It takes the output of the flatten layer and forecasts the best EEG image categorization [17].

3.4.4 Softmax Function is a generalization of the Logistic Function, that transforms a vector of K real values into a vector of K real values that total to 1.The input values can be positive, negative, zero, or higher than one, but the softmax turns them into values between 0 and 1[35].

Finally, each CNN node may learn characteristics from various phases. The data processed in the EEG waveform reconstruction step is the input of the various branches. Following the feature extraction and overfitting reduction stages, the features collected by each branch are combined. The model's outputs are the expected category labels. For the identification of epileptic seizures, we can classify EEG waveforms as normal or abnormal.

4. Implementation

The proposed system is designed using PHP and JavaScript languages. The proposed system can be accessed through mobile application .As well you can access it through the World Wide Web. Finally, it can be used through Personal Computer (PC). Running the proposed system on PC requires the availability of the XAMPP software to convert the PC to server.

The proposed system graphical user interface is shown in figure 5 .Where figure (A) shows the registration process on the system for the first time, in which the identity of the user (doctor - patient - accompanying the patient) is determined, and the language used within the system is determined. As for Figure (B), it shows the method of logging in for a user who is already registered on the proposed system.

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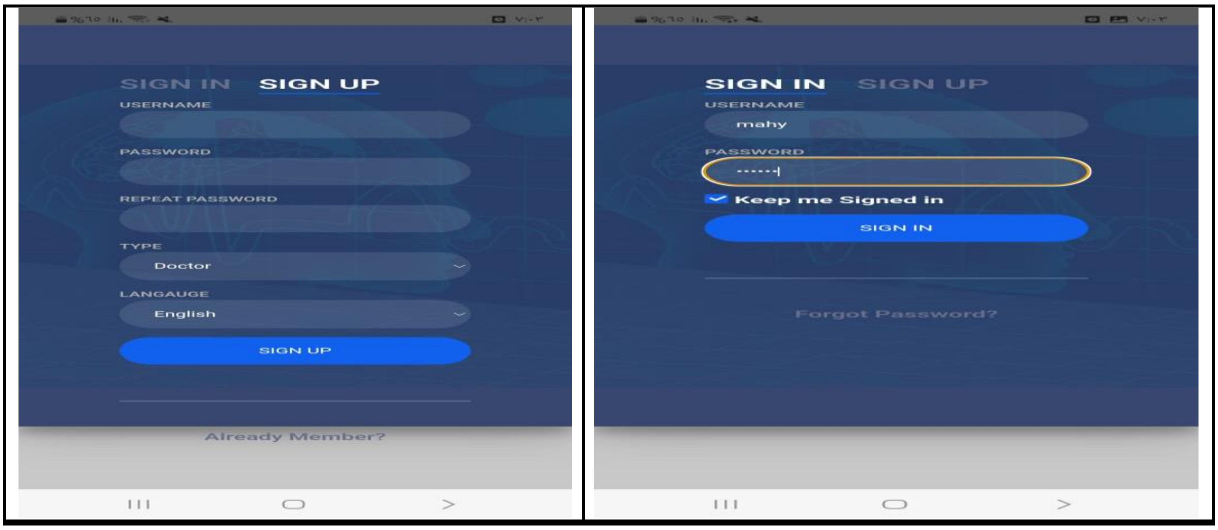

TYPE: Doctor
LANGAUGE: English
USERNAME: mahy

(A)Registration process for first time (B) logging in for users

Figure 5. The Proposed System Graphical User Interface

After the doctor logs in, the following screen appears which contains patient data, with the possibility of adding a new patient, as shown in the figure 6. The figure 7 shows how to upload an EEG image to diagnose epilepsy.

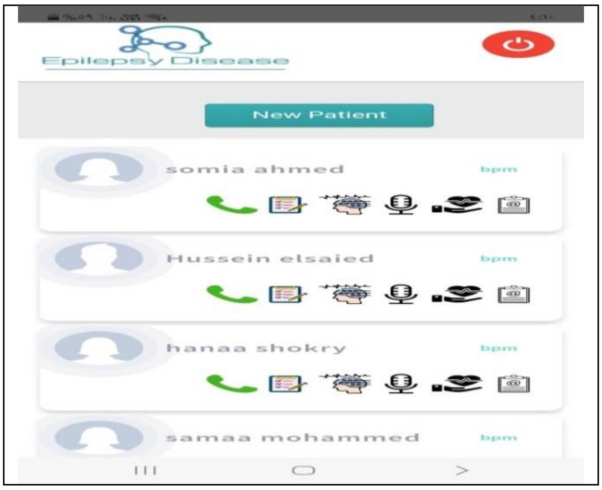

Figure 6. The Proposed System Graphical User Interface for doctor

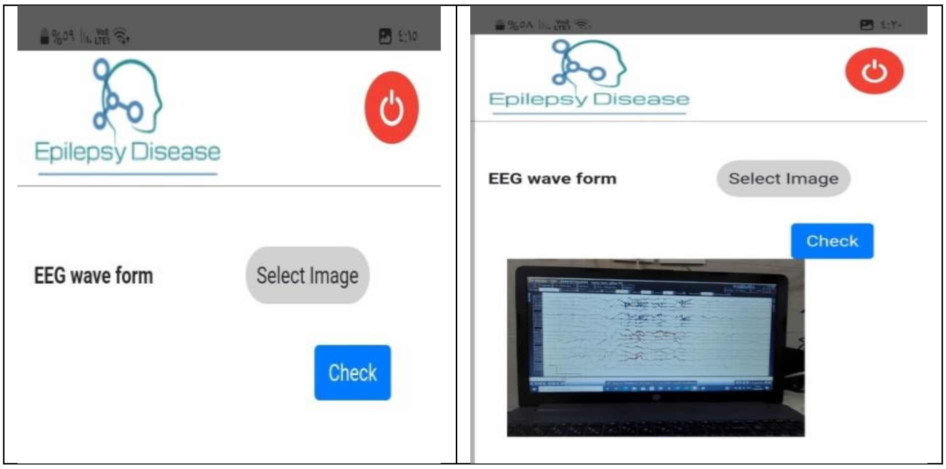

Figure 7. steps for uploading an EEG image to diagnose epilepsy.

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By pressing a check button, the diagnostic result appears (normal or seizure), as shown in figure 8.

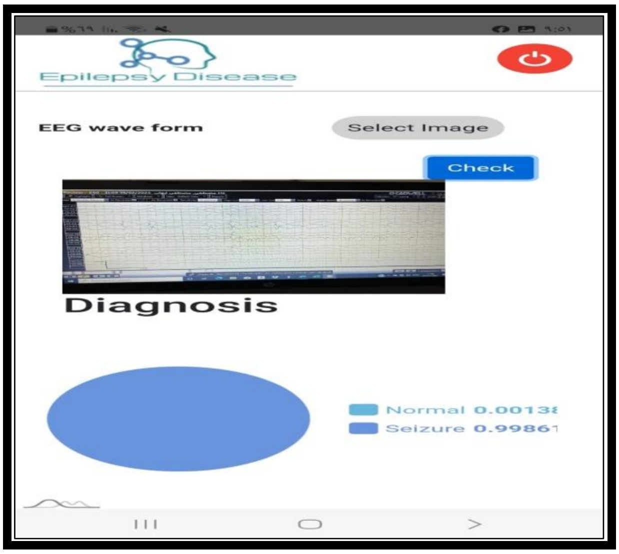

Figure 8. result for classification EEG image

5. Results

In this study, we utilized the EEG dataset from Mansoura University Hospital to train a CNN classifier. The CNN approach proved to be highly effective, achieving an impressive accuracy of approximately 97%. This is illustrated in Figure 9.

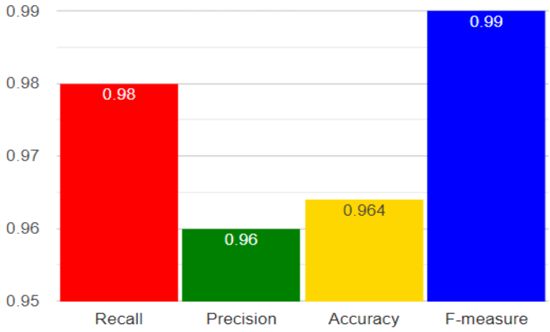

Figure 9. Results for the proposed system

The CNN classifier plays a crucial role in this process. First, the data undergoes preprocessing before being inputted into the classifier to construct their respective models. These models are then employed to classify the data into two categories: non-epileptic (NE) and epileptic (EP).EEG Dataset Description is shown in table 1.

Table 1: EEG Dataset Description.

Set name	**Type of data**	**No. of samples**	**Seizure status**
Set A	Healthy(Normal)	130	Conscious mental state
Set B	PwE(Abnormal)	150	Before and during seizure

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In this study, we analyze the obtained classification results. The EEG datasets were split into two sets: a training set, which accounted for 70% of the data, and a testing set, which accounted for the remaining 30%, as indicated in table 2. The training dataset was utilized to train the model's parameters, while the test dataset was used to evaluate the trained model.

Table 2: EEG images numbers used for the CNN in the proposed system Validation.

	Total number of images	**Number of images used for training**	**Number of images used for testing**
Actual Seizure	150	105	45
Actual Normal	130	91	39

In order to validate the system and measure the classification results, we utilize several metrics: Accuracy, Precision, Recall, and F-measure. These metrics are calculated using equations (5) through (8). Additionally, we can compute these evaluation metrics by analyzing the parameters in the confusion matrix as indicated in Table 3. [17, 20, 36, 37]:

Table 3: The Parameters of Confusion Matrix.

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

In the context of EEG image analysis for seizure detection, we use specific terms to describe the performance of the algorithm. True Positive refers to the number of seizure EEG images that are correctly detected by the algorithm. True Negative represents the number of non-seizure EEG images that the algorithm correctly recognizes. False Negative indicates the number of seizure EEG images that are incorrectly detected as non-seizure. Finally, False Positive denotes the number of non-seizure EEG images that are incorrectly detected as seizure.

$$Accuracy = \frac{True\ positive + True\ negative}{Total\ number\ of\ samples} \tag{5}$$

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \tag{6}$$

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \tag{7}$$

$$F - measure = \frac{2 \times ((Precision \times Recall)}{(Precision + Recall)} \tag{8}$$

Accuracy is a measure of how well the model performs in predicting existing categories during the medical diagnosis test (Equation (5)). It represents the percentage of expected positive cases that are actually positive. The higher the accuracy, the more confident we are in the model (Equation (6)). Recall is another evaluation metric used to determine how well the model can detect true positive labels. It represents the ratio of expected positive categories correctly to all observations in the actual category (Equation (7)). Finally, the F-measure is calculated by taking the weighted harmonic mean of accuracy and recall. It is also used to determine the accuracy of the system, which can range from 1 (best value) to 0 (worst value) (Equation (8)). All results are shown in figure 9.

6. Conclusion and future work

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This paper introduces an automated technique for epilepsy detection that addresses the challenges of binary classification (seizure vs. non-seizure or epileptic vs. non-epileptic). Utilizing deep learning, a state-of-the-art machine learning technology, the proposed method detects epileptic seizures based on the EEG wave pattern for Interictal Epileptiform Discharges (IED). A CNN-based classifier is employed, trained, and tested on an EEG dataset collected from patients at Mansoura University Hospital. The EEG records are converted into images to serve as inputs to the CNN, with a non-local mean filter applied to these images to remove noise. The trained model successfully detects epileptic seizures, achieving an accuracy of approximately 96.4%. This system has demonstrated outstanding performance in helping neurologists-in-training accurately identify epileptic seizures using EEG data and can be easily integrated into real-time diagnostic systems. Future research will focus on enhancing classification by combining EEG data with EEG visuals.

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