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Automated validated tool for epileptic seizure detection using deep learning

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Abstract

This paper explores an innovative approach for the automatic detection of epileptic seizures from audio recordings and Heart Rate Variability (HRV) using Convolutional Neural Networks (CNNs). In medical settings, accurately labeling seizure events is critical for patient monitoring. However, manual annotation by experts is not only time-intensive but also highly repetitive. To address this challenge, we developed a structured questionnaire for patients and eyewitnesses, concentrating on observable characteristics during typical seizure events. This questionnaire was used to prospectively study 198 consecutive adult patients with either Psychogenic Non-Epileptic Seizures (PNES) or Epileptic Seizures (ES). For each question, specific signs, symptoms, and risk factors were extracted as variables. The results showed a sensitivity of 95.10% and a specificity of 97.06%, confirming the reliability of the questionnaire. Also, the method proposed in the study categorizes all seizure vocalizations into a singular target event class, modeling the detection task as a binary classification problem target (seizure event) vs. non-target (non-seizure event). The CNN is trained to detect seizure events in short time frames. Experimental results indicate that the method achieves over 92.5% detection accuracy. Furthermore, the research leverages the correlation between pre-ictal epileptic states and HRV features. By addressing the noise interference commonly present during seizures, the proposed model can robustly train the CNN to identify pre-ictal states. The model's performance is promising, yielding an accuracy of over 91.5% for both positive and negative predictions. The proposed system underwent a human evaluation by a group of physicians at Mansoura University Hospital. The results were highly satisfactory, with the doctors expressing strong approval of the system's performance.

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1. Introduction

Epilepsy is one of the most widespread neurological disorders globally, affecting an estimated 50-70 million individuals. Approximately 2 to 4 million new cases are diagnosed each year [1]. The World Health Organization (WHO) highlights that epilepsy is a treatable condition when accurately diagnosed, with around 70% of individuals potentially living seizure-free lives with appropriate care. Notably, approximately 80% of those affected live in low- and middle-income regions [2, 3].

While medication successfully controls seizures in about 70% of cases, the remaining 30% remain vulnerable to secondary physical injuries. With about 1% of the global population affected by epilepsy, developing wearable technologies to predict seizures and alert patients before their onset could lead to significant societal benefits [4].

Seizures are the hallmark of epilepsy, marked by abrupt, repetitive, and temporary dysfunctions of the central nervous system due to the excessive synchronization of neuronal activity in the brain [5, 6]. Diagnosing these episodes typically involves a comprehensive assessment, including a review of medical history, neurological examination, and diagnostic tests such as Electroencephalograms EEGs to monitor brain activity [7].

Many studies aimed at predicting seizures rely heavily on EEG data, limiting their use in everyday situations. Nocturnal seizures, which often go undetected, have been linked to Sudden Unexpected Death in Epilepsy (SUDEP) [8]. Physical indicators like heart rate and movement [9] are commonly used to detect these seizures. Meanwhile, audio monitoring has gained traction in healthcare as it utilizes nonintrusive acoustic systems traditionally used for nighttime care.

Some studies reveal statistical correlations between HRV features and the preictal and postictal phases of epileptic seizures. Although the exact physiological mechanisms remain unclear, this opens the possibility of predicting seizures using Electrocardiogram (ECG) [10,11].

Artificial Intelligence (AI) has played a pivotal role in telemedicine [12], enabling personalized diagnosis, treatment planning, and disease management [13]. In recent years, machine learning has been widely adopted for seizure detection and prediction [14]. Additionally, emerging research increasingly focuses on deep learning algorithms, which have shown remarkable success in areas like speech recognition and computer vision [15].

Some students in educational institutions are vulnerable to epileptic seizures and often fear experiencing these episodes in front of their peers. As a result, the primary focus of our research is on accurately identifying epileptic seizures through the patient's exhibited symptoms, followed by predicting upcoming seizures using either heart rate monitoring or the sounds the patient makes prior to the onset of a seizure.

This paper presents an innovative method for detecting epileptic seizures through audio analysis by treating various vocalizations during seizures as a unified target class. It approaches the seizure detection problem by modeling it as a binary classification task—seizure (target) versus non-seizure (non-target). The system is built using a CNN, which learns the distinctive acoustic features from a large dataset of annotated patient data. During the detection phase, the method processes lengthy audio recordings (10-14 hours) by segmenting them into shorter intervals for real-time seizure detection.

Furthermore, this paper emphasizes the use of supervised classification techniques to identify pre-ictal Heart Rate (HR) patterns for seizure prediction. A robust method is presented for processing ECG data, which efficiently handles the inherent noise of portable ECG devices and the severe noise that occurs during seizures. The heart rate features extracted from the processed HR data are then used to train the CNN, which performs the seizure prediction task. The term HR refers to the heart rate, while RR represents the interval between successive wave peaks in the cardiac cycle, illustrating heart rate regularity and speed.

In addition, it detects the presence of seizures in patients by analyzing their responses to a questionnaire that includes a range of symptoms specific to epileptic episodes. The proposed technique was evaluated by a group of patients from Mansoura University Hospital.

The system is designed to diagnose seizures and predict forthcoming episodes, ultimately reducing the significant clinical burden on neurologists. Moreover, it aids medical students, less experienced doctors, patients, and caregivers in diagnosing epilepsy and predicting seizures, thereby shortening the time required for diagnosis. The key contributions of this study are as follows:

- Using Rules to assist in analyzing diagnostic questionnaire data.
- Using AI and teachable machine for audio dataset creation.
- Advising smart telemedicine systems on an effective and secure epilepsy detection and diagnostic solution.
- Developing a new framework for reducing the dimensionality of HRV waveform representation and analyzing patient sounds using TensorFlow (TF) and feeding the reduced data into a Convolutional CNN to enhance model efficiency and reduce training complexity.
- Investigating and testing the suggested system in terms of accuracy. We used accuracy, recall and precision to estimate performance.

The remainder of this work is structured as follows. Section 2 provides an overview of related work on seizure detection and predictability. Section 3 discusses the proposed system, including the dataset used. Section 4 presents the application and experimental results. Finally, Section 5 outlines the conclusions drawn from this study.

2. Related Work

It is difficult to distinguish between the possibility of seizures and non-seizures. This requires obtaining and identifying the distinguishing factors from the heart rate pattern and the sounds emitted before the seizure. In this section, we will provide an overview of the advanced methods involved in detecting seizures and non-seizures using different feature extraction and classification algorithms. Dohyun Lee, et.al [16] used a method for predicting epileptic seizures a pre-trained model with supervised contrastive learning and a hybrid ResNet-LSTM model. The approach involves three phases: preprocessing data into spectrograms using STFT, pre-training with augmented data and supervised contrastive loss, and training the hybrid model. This model combines ResNet and LSTM to capture both image and time features. Tested on CHB-MIT and Seoul National University Hospital (SNUH) datasets, the method achieved accuracies of 91.90% and 83.37%, respectively, and outperformed traditional methods. Sina Shafiezadeh, et.al [17] improved seizure forecasting for new patients using a calibration pipeline that fine-tunes deep learning models with just one epileptic event. Testing on two datasets showed over 20% increased accuracy and consistent improvement across patients. The method benefits both deep learning and feature-based machine learning models, requiring only one event per patient for calibration, making it useful for practical healthcare applications. Sona M. Al Younis, et.al [18] used machine learning models KNN, NN, SVM, and TREE to classify LVEF in HF patients based on 24-hour ECG recordings. Data from 303 HF patients were analyzed, with TREE and KNN showing the highest accuracy (91.2% and 90.9%, respectively) and AUROC (0.98 and 0.99). Optimal classification occurred during midnight-1 am, 8–9 am, and 10–11 pm. These results suggest a potential for automated CAD screening aligned with circadian rhythms. Nurul Absar, et al. [19] used four machine learning models Random Forest (RF), Decision Tree (DT), AdaBoost (AB), and K-nearest Neighbor (KNN) to detect heart disease. Evaluated on the Cleveland, Hungary, Switzerland, and Long Beach (CHSLB) datasets from Kaggle, the models achieved accuracies of 99.03% (RF), 96.10% (DT), 100% (AB), and 100% (KNN). On the Cleveland dataset alone, RF and KNN achieved accuracies of 93.44% and 97.83%, respectively. Kunpeng Song, et al. [20] proposed an intelligent epileptic prediction system used Synchrosqueezed Wavelet Transform (SWT) and Multi-Level Feature Convolutional Neural Network (MLF-CNN). It achieved 96.99% accuracy and 96.48% sensitivity on the CHB-MIT dataset, and 94.25% accuracy and 97.76% sensitivity on the ZJU4H dataset, with false positive rates of 0.031% and 0.049% FPR/h, respectively. Xiao Wu, et al. [21] developed a new method for predicting epileptic seizures used successive variational mode decomposition (SVMD) and transformers. The data were decomposed and denoised with SVMD, then input to a pre-trained BERT model. This approach achieved 0.86% sensitivity and 0.18% FPR on intracranial EEG data. Kuldeep Singh, et al. [22] developed a two-layer LSTM model predicted epileptic seizures using spectral features from 23-channel EEG data. Evaluated on 5-50 second EEG segments from 24 subjects, the model achieved 98.14% accuracy, 98.51% sensitivity, and 97.78% specificity. Jaehak Yu, et al. [23] developed a stroke prediction system using real-time bio-signals and Artificial Intelligence (AI). Unlike costly image-based tools, this system utilized Random Forest and Long Short Term Memory (LSTM) algorithms. It achieved prediction accuracies of 90.38% with Random Forest and 98.96% with LSTM. Toshitaka Yamakawa, et al. [24] developed an innovative telemeter measured R-R intervals from ECG, with a smartphone app for calculating heart rate variability in real-time. Tested on seven epilepsy patients, it showed 85.7% sensitivity in detecting heart rate variability changes before seizures. Al-Hammadi [25] analyzed whether the audio recordings of epileptic and psychogenic non-epileptic seizures (PNE) could be classified using linear, quadratic, or support vector machine (SVM) classifiers. In their study, the SVM classifier using four mel-frequency bands achieved an accuracy of 76% during cross-validation. However, the sample size for this analysis was limited to 16 recordings of epileptic seizures and 20 recordings of PNE seizures, suggesting that further research with a larger dataset would be necessary to validate and improve the classifier's performance. Arends et al [26] focused on epilepsy patients with intellectual disabilities, researchers selected 10 adults who exhibited major seizures accompanied by recognizable sounds from an initial group of 17 individuals. These patients were monitored for four weeks using both audio and video recordings. The results showed that audio detection was effective at identifying either the initial vocalization or noise during major seizures. However, since the sounds produced were specific to each patient, the system was only able to reliably detect major seizures in half of the participants. This indicates that while audio monitoring can be useful, the variability in seizure-related sounds between individuals limits its general applicability Bruijne et al [27] analyzed vocalization during seizures, researchers observed vocal sounds in 61 out of 95 seizures across 17 patients. The study employed basic audio statistics derived from 25-millisecond sliding windows, training classifiers to detect specific vocal patterns such as screams, lip smacking, moans, or heavy breathing. Their experimental results achieved precision rates between 66% and 77% using 10-fold cross-validation. However, the precision quickly declined with the introduction of noise, and the classifiers were not tested on unseen data, raising concerns about their generalizability and robustness in real-world conditions.

Based on the recent studies, most feature extraction algorithms are manually crafted and not tailored to the data. Deep Learning (DL) can enhance the accuracy and generalizability of epilepsy detection systems. Hence, we were motivated to leverage deep learning to create a deep model with minimal learnable parameters capable of predicting imminent epileptic seizures.

3. Proposed System

The proposed system is divided into two sections: the first section elucidates the diagnosis of epilepsy, while the second section explains how to detect an upcoming seizure.

3.1 Epilepsy diagnosis through the questionnaire

Questionnaires designed to assess ES and PNES are predominantly used as tools to facilitate faster referrals to specialized epilepsy centers, where diagnosis can be confirmed, rather than serving as standalone diagnostic alternatives. While video-EEG monitoring remains the gold standard for diagnosis, these questionnaires help streamline diagnosis when video-EEG is either unavailable or yields inconclusive results. There are many types of epileptic seizures that epilepsy patients suffer from, and each seizure contains a set of symptoms that indicate the presence of this seizure, such as generalized seizures and partial seizures. In the proposed system, epileptic seizures were dealt with in general. The questionnaire within the proposed system consists of a set of questions that were created by a group of experts in the medical field. A total of 105 patients of varying ages, who were diagnosed with epilepsy by neurologists at Mansoura University Hospital based on established medical criteria, were selected. Additionally, 98 patients without epilepsy who regularly attended the outpatient clinics at Mansoura University Hospital were also included in the study.

By conducting several personal interviews with experts in the medical field specializing in epilepsy patients, the most common symptoms in epilepsy patients were obtained, which included a group of symptoms that appear during epileptic seizures, and the following table 1 shows some of the most common symptoms during true and pseudo epileptic seizures.

Table 1: Samples for symptoms of true and pseudo epileptic seizures

No.	Symptoms for true seizure	Symptoms for pseudo seizure

Symptom		
1	Seizure take Briefer time	Seizure take prolonged time
2	Stereotypic the form of symptoms that occur during seizure	Fluctuating the form of symptoms that occur during seizure
3	Epileptic seizure may occur in sleep or wakefulness	Epileptic seizure usually during wakefulness
4	Unaware of what is happening during seizure	Aware of what is happening during seizure
5	Convulsions occur at the time of seizure as abrupt	Convulsions occur at the time of seizure as gradually
6	Movement of the head during the seizure as Side to side with staring	Movement of the head during the seizure one way or fixed
7	Movements of the hands and feet during the seizure organized movements	Movements of the hands and feet during the seizure random movements
8	Seizure occurs during sleep	Seizure doesn't occur during sleep
9	Seizure doesn't occurs during pseudo sleep	Seizure occurs during pseudo sleep
10	Difficult to describe the beginning of the seizure	Factual description the beginning of the seizure
11	Synchronized the movements during the seizure	Lack of synchronization of movements during the seizure.
12	No response to any action during the seizure	Defense any action during the seizure
13	Tongue biting through lateral	Tongue biting through apical
14	Eyes open during the seizure	Eyes close during the seizure
15	Shape of the pupil of the eye is abnormal	Shape of the pupil of the eye is normal
16	Increasing in heart rate	Normal heart rate
17	Feeling a headache during the seizure	Don't Feel a headache during the seizure
18	clinch teeth	No teeth clenching occurs.
19	Doesn't make sounds during the seizure	Make sounds during the seizure
20	Make sounds at beginning of the seizure	Make sounds during or after seizure
21	Doesn't remember what happened during the seizure	remember what happened during the seizure
22	Occur incontinence	Rare incontinence
23	Injuries occur during a seizure.	Don't injuries occur during a seizure.
24	Long time take to recover from a seizure	Little time take to recover from a seizure

According to the human expert every symptoms has weight (-1 or 1) for pseudo-seizure and (1 or 24) for true seizure. The knowledge base of epileptic seizure symptoms was built using rules to obtain the probabilities of different symptoms appearing together, in order to confirm whether it is a true or pseudo seizure. A specific weight was assigned to each symptom, distinguishing between real and pseudo-seizures. Ultimately, the cumulative weights were calculated, and the final result of the questionnaire was determined accordingly. Additionally, certain symptoms serve as definitive indicators of an epileptic seizure. If any of these symptoms are present, whether individually or in combination, they confirm the occurrence of a seizure.

The results led to the identification of several key symptoms, which formed the foundation of the knowledge base. The table 2 presents samples of this knowledge base, utilized for distinguishing true epileptic seizures from pseudo-seizures.

Table 2: system knowledge base obtained from the symptoms of true and pseudo epileptic seizures

Symptoms (No)	Rules
S(2)	True epileptic seizures

S(4)	Pseudo epileptic seizures
S(5)	Pseudo epileptic seizures
S(8)	True epileptic seizures
S(12)	Pseudo epileptic seizures
S(13)	True epileptic seizures
S(14)	True epileptic seizures
S(17)	Pseudo epileptic seizures
S(22)	True epileptic seizures
S(23)	True epileptic seizures
S(2)^ S(8)	True epileptic seizures
S(2) ^ S(8)^ S(13)	True epileptic seizures
S(2)^ S(8)^ S(14)	True epileptic seizures
S(13)^ S(14)	True epileptic seizures

3.2 Epilepsy prediction through HRV

In the proposed system, the main purpose is to predict epileptic seizures with tunable parameters on the measured HR. The proposed system contains the modules to read and process the incoming HR data as well as to send the alarms as shown in figure1.

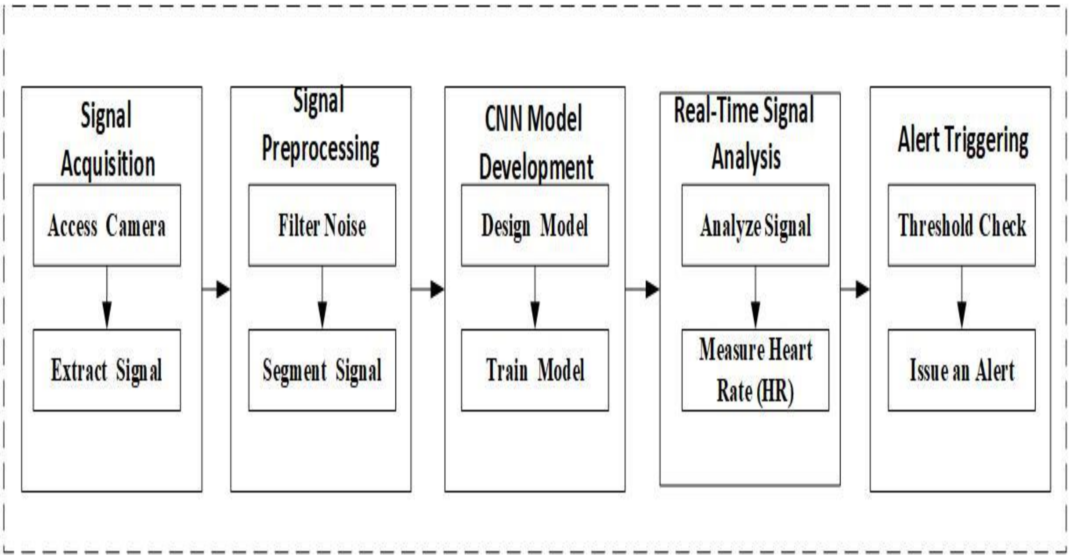


Figure 1. Heart rate measurement architecture

Signal Acquisition

- Access Camera: an Android device's camera with a resolution of 32 megapixels and an aperture of F/2.2 support PhotoPlethysmoGraphy (PPG) was utilized ‹which generally captures ECG signal for fifteen seconds from the thumbs at a sampling frequency of 250 Hz, which is done in sitting position with hands resting on a table.
- Extract Signal: Transform the captured video frames into a PPG signal by analyzing light absorption variations associated with heartbeats.

Signal Preprocessing

- Filter Noise: Implement signal processing techniques, such as bandpass filtering, to eliminate noise and isolate relevant HRV components. This is a signal processing technique that allows frequencies within a specific range to pass through while attenuating frequencies outside that range. It is commonly used in ECG signal processing to isolate the frequency components that are most relevant for heart rate and other physiological measurements, typically between 0.5 to 40 Hz. The general transfer function for a second-order bandpass filter can be expressed as [28]:

$$H(s) = \frac{A \cdot S \cdot Q}{S^2 + \frac{\omega 0}{Q} . S + W_0^2} \qquad (1)$$

Where:

H(s) is the transfer function.

S is the complex frequency variable.

A is the gain.

w_0 is the center angular frequency.

Q is the quality factor, which determines the bandwidth of the filter.

- Segment Signal: Partition the signal into specific time windows for detailed analysis.

CNN Model Development

- Design Model: Construct a CNN trained to identify patterns in HRV signals that suggest a forthcoming epileptic seizure.
- Train Model: Train the model using a dataset of HRV signals annotated with normal and seizure-related events.

Real-Time Signal Analysis

- Analyze Signal: Input real-time HRV data from the camera into the trained CNN model for classification.
- Measure HR: Determine the HR by detecting peaks and calculating the intervals between them.

Alert Triggering

- Threshold Check: Continuously monitor HR, and if it surpasses 120 bpm depend on equation (new HR > last HR*0.2+last HR); treat it as a potential warning of an impending seizure.
- Issue an Alert: Activate an alert for the user or caregiver if the HR exceeds the set threshold.

3.3 Epilepsy prediction through sound classification

This section of the proposed system presents an innovative approach to epileptic seizure detection by leveraging audio data, where various seizure-related vocalizations are treated as a unified target event.

The method employs a CNN to learn and differentiate the acoustic features, utilizing an extensive dataset of annotated patient recordings. During the detection phase, the system processes prolonged audio recordings (ranging from 10 to 14 hours) and identifies seizures by analyzing short time segments within these recordings.

Sound event detection involves identifying the start and end of specific sound events by analyzing their acoustic characteristics. In the proposed system, an epileptic seizure is treated as a target sound event to be detected within an audio recording. To detect a seizure, the audio is segmented into short clips, and features are extracted from each segment. The CNN is trained on these features, and during the testing phase, it evaluates whether the target event is present in segments of the same duration as those used in training.

For this study, a segment length of 10 seconds was chosen, as it provides sufficient audio content for effective training of the neural network. This approach achieves detection with a temporal resolution of 10 seconds, rather than pinpointing the exact onset and offset of the seizure. Figure2 presents the block diagram for prediction seizure through sound, with training and testing branches illustrated separately.

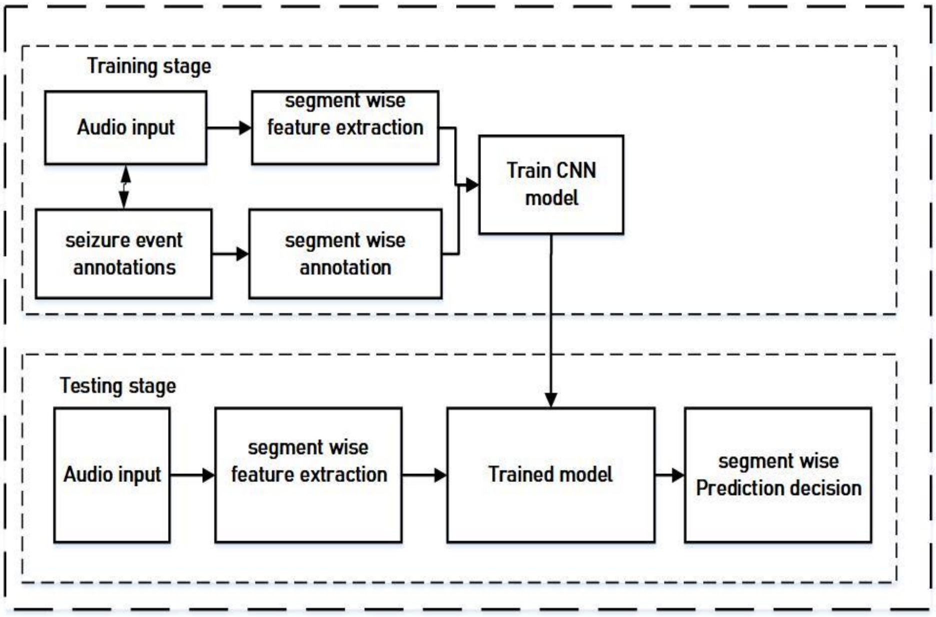


Figure 2. block diagram for prediction seizure through sound

The convolutional layers of the CNN are responsible for learning these features, with kernels extending across both the frequency and time axes to capture the relevant temporal characteristics of the target class.

During training, the target output for each segment is set to >=0.65 when a seizure event is active and 0 when it is inactive, this percentage was chosen to provide a more accurate prediction of the upcoming seizure, following multiple applications. After each CNN layer, a max-pooling operation is applied along both axes to reduce data dimensionality. Batch normalization is performed after each convolutional layer to normalize the layer inputs, and the Rectified Linear Unit (ReLU) activation function is employed.

To prevent overfitting, a 30% dropout is implemented after each layer. The output layer consists of a single sigmoid unit, producing a binary result that indicates whether the target class is active or inactive.

Once the CNN has processed the input and produced a binary output indicating whether the target class (seizure event) is active or inactive, the system proceeds to the alert stage. If the output of the CNN is >=0.65, signaling that a seizure event is detected, the system immediately triggers an alert.

The alert is designed to be both rapid and reliable, ensuring that the patient and their caregivers can take appropriate action swiftly to mitigate the risks associated with the seizure.

The pseudo code for some sections of this paper is presented in the following part.

Algorithm1.Epilepsy diagnosis through the questionnaire	**Algorithm2.**Epilepsy prediction through HRV
Input: *patient_id, P.S.V* *//P.S.V refer to patient symptoms vector* ***Output:*** *Decision* *// Decision will be true seizure or pseudo seizure* ***Begin*** *Define T.P.S array symptoms [24, 2]* *// T.P.S refer to seizure and pseudo symptoms* *// T.P.S array components are (id, true seizure weight, pseudo seizure weight)* *I=0* *For each item in P.S.V* *If item="a" then total T.S +=W.T.S (i, 1)*	***Input:*** *finger video* ***Output:*** *Decision* *// Decision will be alarm or normal* ***Begin*** *Apply frompixels() for figure video to convert it into a tensor* *// a tensor is captured image data* *Apply crop Image () for a tensor to crops and resizes it* *Apply a bandpass filter () for a tensor to remove noise* *Load TensorFlow js for pulse model* *Apply predictpulse() a tensor to calculate newHR* *Connect with database*

// T.S refer to true seizure	*Select HR-day , HR for patient p*
// W.T.S refer to weight of true seizure	*If Hr-day is current day then*
Else total P.S += W.P.S (i, 2)	*If (new HR>HR+(HR*0.2)) then give alarm*
// P.S refer to pseudo seizure	*Else show "normal"*
// W.P.S refer to weight of pseudo seizure	*End if*
End if	*Else insert new HR & current day in HR-day for patient p*
i+=1	*End if*
Next item	
If total T.S>total P.S then	
Decision= "true seizure"	
Else Decision= "pseudo seizure"	
End if	

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 can be used by neurology students, nurses, patients, or anyone interested in the management of epilepsy. Graphical user interface of mobile application system will be illustrated in this section.

The user will be able to log into the system after loading the proposed system and will be able to traverse the system. To log in, the user must first enter his user name and password into the designated fields and then click the "Log in" button, as shown in Figure 3 ،assuming he is already registered in the proposed system.

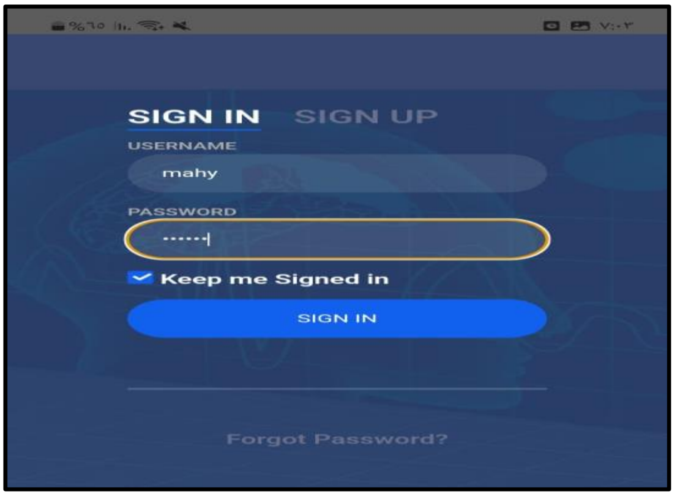


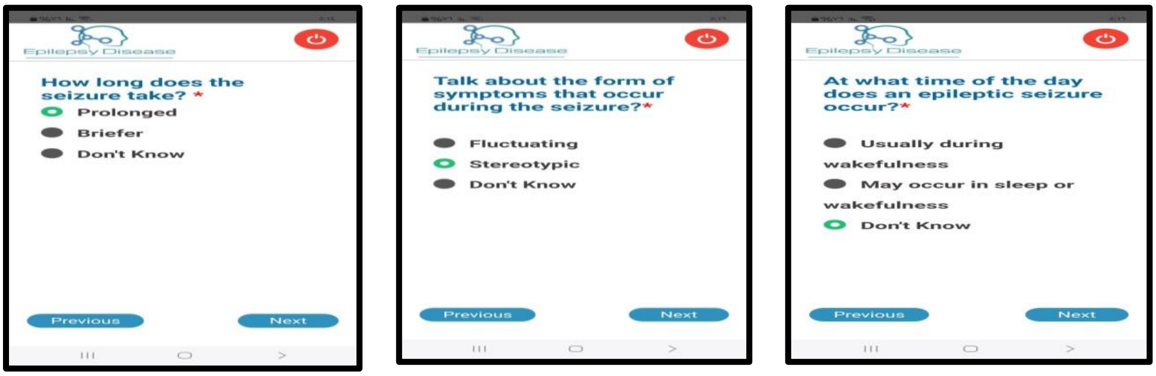
Figure 3. The Proposed System Graphical User Interface

4.1 Diagnosing epilepsy through its symptoms

Diagnosing epilepsy through questionnaire is performed according to the following steps:

- Access the Diagnostic Questionnaire: Navigate to the section dedicated to the epilepsy diagnostic questionnaire.
- Complete the Questionnaire: Answer all relevant questions regarding the patient's symptoms, medical history, and other pertinent details.
- Submit the Responses: Review the completed questionnaire and submit it for analysis.
- Review Diagnostic Results: Analyze the results generated from the questionnaire to assist in diagnosing epilepsy.

This process helps in assessing the likelihood of epilepsy based on the patient's responses and medical history. Figure 4 (a, b, c) shows a sample of the questionnaire questions and their answers.



(a) (b) (c)

Figure 4. samples of questionnaire questions and their answers.

4.2 Predicting an epileptic seizure through heartbeat

To predict an epileptic seizure through heart rate monitoring, follow these steps as depicted in the figure 5 displays the start screen, where heart rate (HR) is recorded. Figure 6 shows the recorded heart rate results, presenting various screens for a single patient at different times.

- Collect Heart Rate Data: Begin by monitoring and recording the patient's heart rate using the application, initiated by pressing the "Start Camera" button.
- System Data Upload: The system automatically inputs the recorded heart rate data into the application, where it is analyzed and stored in the patient's database. If it is the first measurement of the day, the system records it directly as the baseline for that day. However, if it is not the first measurement, the system compares the current reading with the last recorded result taken on the same day to detect any significant changes or trends.
- Generate Predictions: The system analyzes the heart rate patterns to assess the likelihood of an impending seizure and give alarm.

Monitoring heart rate can offer crucial insights into potential seizure activity, thereby enhancing the ability to anticipate and manage epileptic events more effectively.

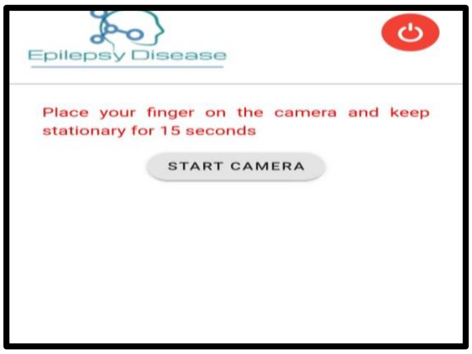
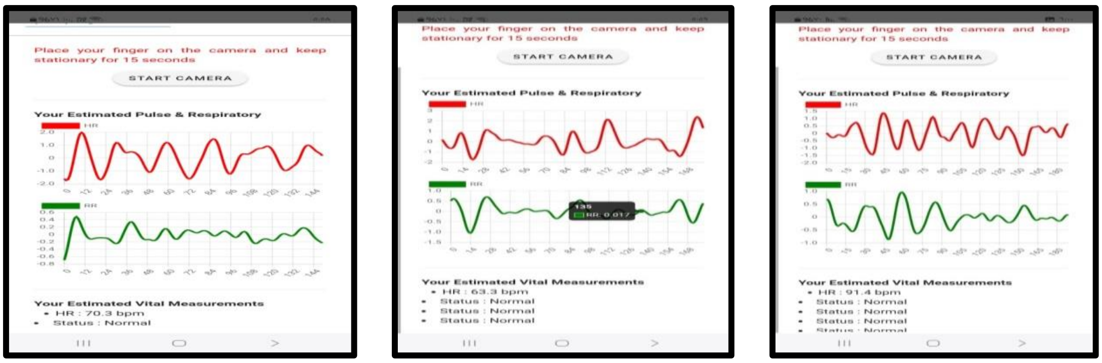


Figure 5. Heart rate measurement



(a) (b) (c)

Figure 6. Heart rate measurement result for the same patient

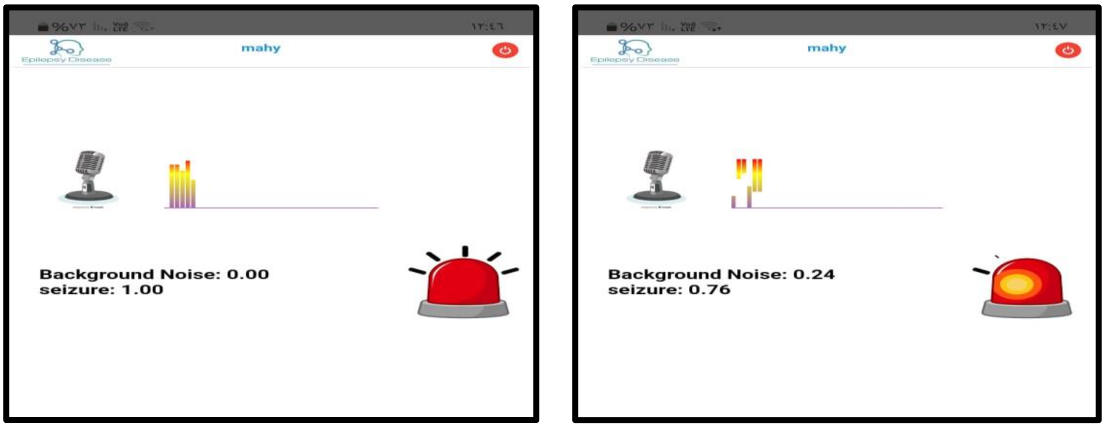
4.3 Predicting an epileptic seizure patient's voices

To predict epilepsy by analyzing the sounds a patient makes before a seizure, follow these steps as depicted in the figures 7 ،8 ، 9:

- Acoustic data collection: Record the patient's sounds using the app, ensuring accurate capture of any vocal phenomena that may precede a seizure.
- Upload audio data to the system: The recorded audio files are sent to the application for analysis, where they are processed.
- Voice Pattern Analysis: The system examines voice data to identify patterns or anomalies associated with seizure activity.
- Generate predictions: Based on the analysis, the system predicts the probability of an impending attack and give alarm.

Analysis of pre-seizure sounds can provide valuable insights for predicting seizures, and improving the management and prediction of epileptic events.

Figure 7. recording the patient's voice



(a) (b)

Figure 8. predicting an impending seizure

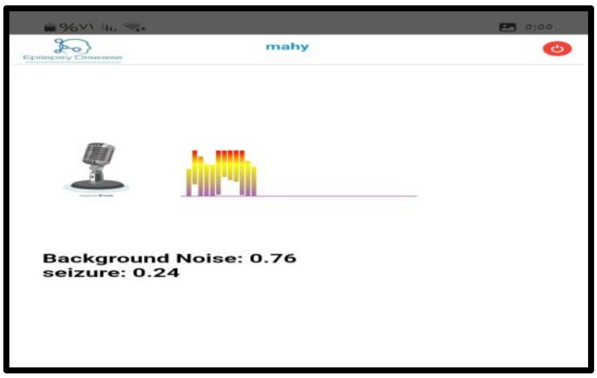


Figure 9. predicting the occurrence of a non-epileptic seizure

5. Results

5.1 Results for diagnosing epilepsy through questionnaire

To validate the questionnaire a transversal observational study was carried out. The central question of the questionnaire was: "During the last 24 months, while you are stopping treatment, have you had convulsions or epileptic seizures, brief periods of loss of consciousness, involuntary spasms of the arms or legs, or have you appeared to be disconnected from reality or incapable of responding?" If the answer was negative the interview was concluded and the patient was considered not to suffer from epilepsy. If the answer was positive, the patient was considered to be at risk of having seizures, and the interview proceeded to the following series of questions Table 3, whose objective was to establish the diagnosis of epilepsy.

Table 3: Complementary questions to establish the diagnosis of epilepsy.

No. question	Question
1	How long does the seizure take?
2	Talk about the form of symptoms that occur during the seizure?
3	Are you aware of what is happening around you during a seizure?
4	When do convulsions occur at the time of seizure?
5	Describe the movement of the head during the seizure?
6	Describe the movements of the hands and feet during the seizure?
7	Does the seizure occur during sleep?
8	Does the seizure occur during pseudo sleep?
9	Describe the beginning of the seizure?
10	Are the movements synchronized during the seizure?
11	Talk about his response to a specific action such as holding hands?
12	Where is the tongue biting?
13	What is the condition of the eyes?
14	Explain the shape of the pupil of the eye?
15	Is there an increase in heart rate?
16	Do you feel a headache during the seizure?
17	Does clinch your teeth?
18	Do you make sounds during the seizure?
19	When do you make sounds at the time of the seizure?
20	Do you remember what happened during the seizure?
21	What about incontinence?
22	Are there injuries caused by the seizure?
23	How long does it take to recover from a seizure?

A total of 105 patients of varying ages, who were diagnosed with epilepsy by neurologists at Mansoura University Hospital based on established medical criteria, were selected. Additionally, 98 patients without epilepsy who regularly attended the outpatient clinics at Mansoura University Hospital were also included in the study.

In both instances, patient selection was conducted consecutively, adhering to the standard procedures set by the administrative staff during 2023. In all cases, valid consent was obtained from the patient or a relative. Patients were excluded if their relatives or representatives could not provide reliable information.

A pilot test was performed involving the relatives of five patients with epilepsy and five non-epileptic patients to adjust the details and address any potential uncertainties that could emerge during the application of the questionnaire.

For the study, no more than four individuals from each group, along with their relatives or representatives, were invited daily to the Neurology outpatient clinic at Mansoura University Hospital. The procedure was explained to them, and they were requested not to disclose the patient's diagnosis during the interview. The responses were then recorded in a database created using php My Admin.

Additionally, the neurological doctors re-evaluated a sample composed of 20% of the patient of each group, with the objective of determine the diagnostic reliability of the questionnaire.

The validity of the questionnaire was measured by means of its sensitivity (capacity of detecting patients with epilepsy), specificity (capacity of not diagnosing an epilepsy-free patient as having epilepsy), and the prognostic value of a positive or negative result, which were calculated from the equations shown below .As referential criteria to calculate these measurements, the clinical diagnosis of epilepsy patients diagnosed by a neurologist was used to test the reliability of the questionnaire [29].

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)$$

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad (3)$$

$$Positive\ Predictive\ Value = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (4)$$

$$Negative\ Predictive\ Value = \frac{True\ Negatives}{True\ Negatives + False\ Negatives} \quad (5)$$

$$Index\ of\ Validity = \frac{(True\ Positives + True\ Negatives)}{Total\ Number\ of\ Cases} \quad (6)$$

5 of the 203 evaluated patient lacked complete or reliable information, so they were not taken into account for the analysis. At the end, the study groups consisted of 102 with epilepsy, according to the diagnosis of the neurologists, and 96 without epilepsy. Table 4 show that 100 patient (51%) were between 19 and 30 years of age, and 98 (49%) were between 31 and 60.

Table 4: Composition of the study groups according to age

Age group	Epilepsy patients	Patients without epilepsy	Total
19-30	**50**	**50**	**100**
31-60	**52**	**46**	**98**
Total	**102**	**96**	**198**

The evaluated questionnaire accurately diagnosed 97 individuals with epileptic seizures, resulting in 3 false positive cases. Additionally, 93 individuals were correctly diagnosed as not having epileptic seizures, with 5 false negative cases, as detailed in Table 5.

Table 5: Results of the application of the diagnostic questionnaire in patient with epilepsy and without epilepsy

Diagnosis according to the questionnaire	Patient with epilepsy	Patient without epilepsy	Total
Positive	**97**	**3**	**100**
Negative	**5**	**93**	**98**
Total	**102**	**96**	**198**

The tests of validity of the diagnostic questionnaire demonstrated its satisfactory sensitivity 95.10% and specificity 97.06%. The index of validity was of 96.08%, and the prognostic value of a positive result of 97.00% and that of a negative result of 95.19% as shown in figure 10

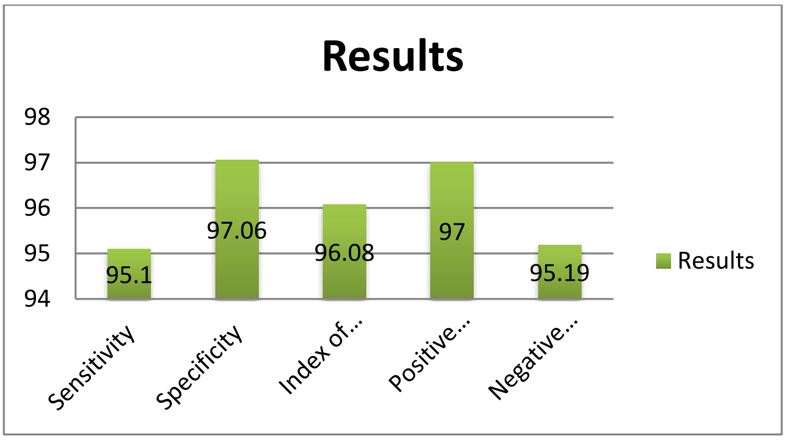


Figure 10. Results for the proposed system (Diagnosing epilepsy through questionnaire)

5.2 Results for prediction epilepsy through ECG classification

To evaluate the proposed application, it was implemented on 30 patients (20 men and 10 women) aged between 20 and 65 years, who were attending Mansoura University Hospital. Table 6 presents the number of patients who participated in the study and were subjected to the proposed application for predicting epileptic seizures. It serves as a foundation for comparing the results with those obtained using existing applications to ensure the validity and reliability of the proposed system.

Table 6: numbers of patients who participated in the study

Male	**Female**	**Total**
20	**10**	**30**

The application successfully captured heart rate data and identified significant increases in heart rate that preceded seizure events. On average, the heart rate increased by 30% before a seizure.

To verify the reliability of the results, they were compared with those obtained from the same patients at the same time using some pre-existing applications available on app store. That are widely used and approved for similar purposes. The measurements were also compared to those obtained by the neurologist using the Mansoura University hospital's CADOO device, which measures patients' heart rates through electrocardiography.

The following table 7 compares the results obtained from the proposed system with those other applications. We utilize several metrics: Accuracy, Precision, sensitivity and specificity. These metrics are calculated using equations (7, 8) and equations (2, 3). Also figure 11 shows the results [26].

$$Accuracy = \frac{True\ positive + True\ negative}{Total\ number\ of\ samples} \tag{7}$$

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \tag{8}$$

Table 7: comparing the results of the proposed system with other systems

App	Accuracy	Precision	sensitivity	specificity
Proposed system	**91.5%**	**90.3%**	**93%**	**90%**
Instant Heart Rate	**88.5%**	**87.4%**	**90%**	**87%**
Heart Rate Monitor	**91%**	**89.4%**	**93%**	**89%**
Runtastic Heart Rate Monitor	**89.5%**	**87.6%**	**92%**	**87%**
Heart Rate Plus	**84%**	**83.3%**	**85%**	**83%**

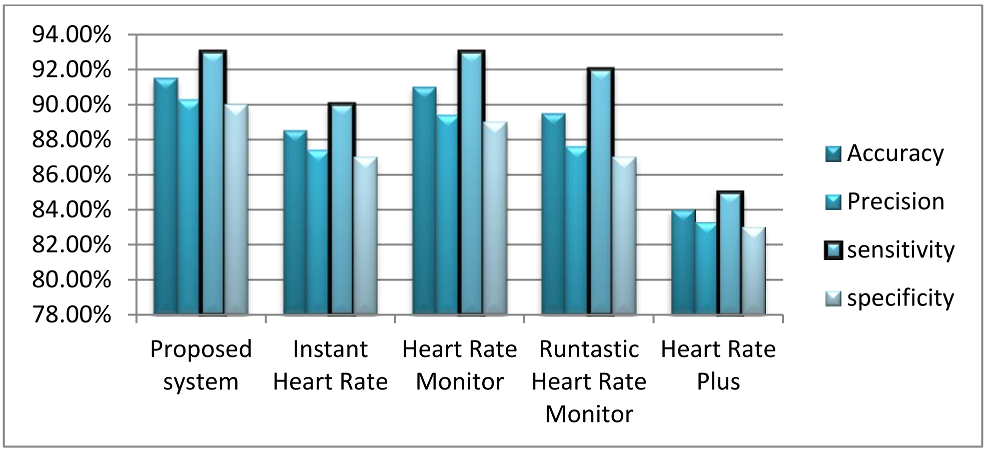


Figure 11. Results for the proposed system (prediction epilepsy through ECG classification)

This comparison highlights the effectiveness of the proposed application in predicting epileptic seizures by monitoring heart rate, demonstrating its accuracy relative to other widely used applications available on app stores.

Our application showed higher accuracy in predicting seizures, with a sensitivity of 93% and a specificity of 90%, outperforming other applications in comparison to the CADDO device located in Mansoura University Hospital. Also Patients reported ease of use and confidence in the application's predictions. No adverse events or technical issues were encountered during the testing period.

5.3 Results for prediction epilepsy through sound classification

The dataset utilized in this study comprises audio recordings from 20 patients experiencing seizures. The recordings were captured during nighttime monitoring sessions at the patients' residences, with each session lasting approximately 10 to 14 hours. The audio data, extracted from corresponding video recordings, was meticulously annotated by certified neurologists at Mansoura University Hospital. A total of 50 seizure events were identified and labeled based on visual cues observed in the video recordings.

Each seizure event was identified and annotated by the neurologists based solely on visual cues observed in the video recordings. Subsequently, these annotations were directly applied to the extracted audio clips. For the purpose of training the seizure detection model, the annotated seizure events were segmented from the audio recordings, with an additional 120-second non-seizure segment included both before and after each seizure event. This padding served as an example of the non-target class, providing the model with necessary context information. Consequently, the final dataset comprised 50 seizure segments and 100 non-seizure segments, ensuring a balanced representation for model training indicated in table 8. The training dataset was utilized to train the model's parameters, while the test dataset was used to evaluate the trained model.

Table 8: numbers of sounds used for the CNN in the proposed system validation.

	Total number of sounds	Number of sounds used for training	Number of sounds used for testing
Actual Seizure	**50**	**45**	**5**
Actual Normal	**100**	**94**	**6**

Given that the seizure events are relatively short, typically lasting between 10 and 30 seconds, the inclusion of the 120-second padding resulted in a sufficient degree of data imbalance within the dataset. This structure ensured that each audio file contained a balanced mix of seizure and non-seizure data, which is essential for training the model effectively.

The proposed Convolutional Neural Network (CNN) model was trained and evaluated using the prepared dataset to predict upcoming seizures based on pre-seizure audio signals. In order to validate the system and measure the classification results, we utilize several metrics: Accuracy, Precision, Recall, and F-measure, yielding the metrics which shown in figure 12.

These results indicate in this section of study, the CNN model effectively distinguishes between seizure and non-seizure events based on pre-seizure audio cues. Achieving an impressive accuracy of approximately 92.5%%.

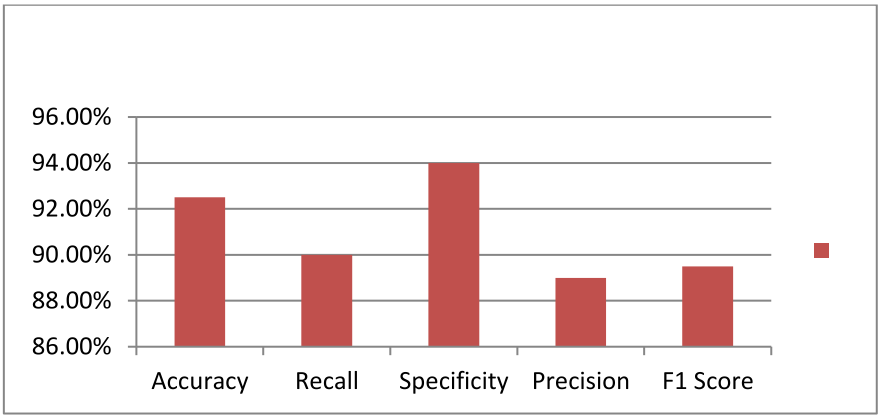


Figure 12. Results for the proposed system (Diagnosing epilepsy through EEG wave form)

Upon detection of a seizure event by the CNN model, the system successfully triggered alerts with a latency of less than 2 seconds in 95% of the cases, ensuring timely notifications to patients and their relatives. The alert system maintained a reliability rate of 93%, minimizing false alarms and ensuring that alerts were only issued when a true seizure event was predicted.

The proposed system underwent a comprehensive evaluation by a team of eight physicians at Mansoura University Hospital, each possessing different levels of expertise in neurology and epilepsy care. This evaluation was conducted to assess the system's full functionality, including its diagnostic accuracy and ability to predict epileptic seizures. The feedback from the doctors was highly positive, as they found the system to be reliable and valuable across varying clinical experiences. The inclusion of physicians with diverse expertise ensured a well-rounded assessment, further validating the system's effectiveness in real-world medical settings. The following Table 9 presents the items of the arbitration form and the doctors' evaluation of it.

Table 9: percentage of responses for each question based on the evaluation results.

Question	**Excellent (%)**	**Good (%)**	**Satisfactory (%)**	**Needs Improvement (%)**
Clarity of the User Interface	**50.0**	**37.5**	**12.5**	**0.0**
Ease of Use for Your Role (e.g., Patient, Nurse, etc.)	**50.0**	**25.0**	**25.0**	**0.0**
Accessibility of the Application	**50.0**	**25.0**	**25.0**	**0.0**
Efficiency in Diagnosing Epilepsy (e.g., through EEG or Questionnaire)	**25.0**	**37.5**	**37.5**	**0.0**
Efficiency in Detection Epilepsy (e.g., through EEG or Questionnaire)	**25.0**	**50.0**	**25.0**	**0.0**
Accuracy in Epilepsy Diagnosis via Symptoms/Questionnaire	**25.0**	**50.0**	**25.0**	**0.0**
Accuracy in Epilepsy Diagnosis via EEG Analysis	**0.0**	**75.0**	**25.0**	**0.0**
Effectiveness in Predicting Upcoming Seizures (e.g., based on heart rate, sound analysis)	**12.5**	**37.5**	**25.0**	**25.0**
Responsiveness of the Application's Alert System	**25.0**	**37.5**	**37.5**	**0.0**
Did the application help you understand your condition better?	**12.5**	**50.0**	**37.5**	**0.0**

Did the application's predictive alerts improve your management of seizures?	**12.5**	**62.5**	**25.0**	**0.0**
Did the application assist in diagnosing epilepsy accurately?	**12.5**	**62.5**	**25.0**	**0.0**
Overall Rating of the Application:	**12.5**	**50.0**	**37.5**	**0.0**

6. Conclusion

This study successfully demonstrates that automatic detection of epileptic seizures using CNNs on audio recordings and HRV analysis is feasible and effective, addressing the limitations of time-intensive, manual annotations. The structured questionnaire developed for observable seizure characteristics proved highly reliable, achieving an impressive sensitivity of 95.10% and specificity of 97.06%. The binary classification approach categorizing seizure-related sounds, along with leveraging HRV features to detect pre-ictal states, enabled the model to maintain robust accuracy, with detection accuracy exceeding 92.5% and predictive accuracy over 91.5% despite noise interference. The system's strong performance, validated by physician feedback at Mansoura University Hospital, highlights its potential for clinical use in patient monitoring.

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