SSRG International Journal of Electronics and Communication Engineering Volume 12 Issue 1, 14-32, January 2025
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I1P102

Original Article

Modelling and Analysis of Magnitude-Squared Wavelet Coherence data for Biomedical Applications

Polepogu Rajesh[1], Vaegae Naveen Kumar[2]

[1,2]*School of Electronics Engineering, Vellore Institute of Technology, Vellore, Tamilnadu, India.*

[2]*Corresponding Author : vegenaveen@vit.ac.in*

Received: 06 November 2024 Revised: 12 December 2024 Accepted: 03 January 2025 Published: 30 January 2025

Abstract *- One of the most persistent neurological diseases is epileptic seizures, which have an impact on people's daily lives by endangering them with frequent seizures. In recent years, seizure detection techniques have been categorized into a number of groups, mainly rational function, empirical mode decomposition, wavelet (time-frequency), time, and frequency. Current diagnostic techniques have focused on developing techniques for electrocardiograms (ECGs) and electroencephalograms (EEGs) due to their noninvasiveness and their capacity to provide repetitive patterns of epileptic-related electrical information. In this work, Power Spectrum Density Estimation (PSDE) is used to examine the magnitude squared wavelet coherence (MSWC) between the ECG and EEG during an epileptic seizure in the typical frequency range of 0–128 Hz. The datasets used in this work are PhysioNet and "N&C-TEC: ECG and EEG files". Mendeley data are used to collect all signals from epileptic seizure patients aged 3 to 25 at Children's Hospital Boston at a sampling rate of 512 samples/second. Each signal is comprised of 30 seconds (15,360 samples). The mean values of the MSWC between the ECG and EEG are calculated. According to the measurement, the MSC values between the ECG and EEG signals in epileptic seizure sample-1 are 0.05, 0.1, and 0.4. Similarly, in epileptic seizure sample-2, MSC values are 0.4 and 0.55; in sample-3, MSC values are 0.15 and 0.4, respectively, in the frequency range of 0 to 128 Hz. Finally, the mean of the MSC value between the ECG and EEG for the first sample, second sample, third sample, and fourth sample is less than 0.55. It shows that the coherence value between the circulatory system and the central nervous system is diminished in epileptic seizure patients, i.e., the coherence between the heart and brain is very low in seizure patients.*

Keywords *- Electrocardiogram (ECG), Electroencephalogram (EEG), Heart Rate Variability (HRV), Fast Fourier Transform (FFT), Morlet Wavelet, Magnitude Squared Wavelet Coherence (MSWC), Seizures, Epilepsy.*

1. Introduction
1.1. Motivation

One of the most important neurological diseases that has detrimental effects on the human nervous system is epilepsy. Individuals of all ages are affected by this lifelong, non-communicable brain disease. Based on the latest data from the World Health Organization (WHO), between 60 and 70 million individuals globally, or around 2% of the total population, suffer from epileptic seizures. After cerebrovascular accidents, epilepsy and Alzheimer's disease is presently the third leading neurological disorder in the US; thus, It is among the most prevalent neurological conditions in the world [1]. 85% of those affected live in developing nations, which adversely impacts their efficiency and the standard of their existence.

Globally, there are 3 million new cases of epilepsy each year, with 10 million of them living in India [2-3]. Epilepsy is predicted to strike 1 in 26 Americans at some point during their lifetime. In lower-middle-income countries, more than 80% of the population suffers from epilepsy. The risk of dying young is almost three times higher for people with epilepsy than for the general population. 75 percent of epileptics in low-income countries do not obtain the appropriate care.

There is stigma and discrimination against people who have epileptic seizures along with their loved ones everywhere in the world. Statistics show that 70% of people with epilepsy could avoid having seizures if their condition was appropriately identified and managed.

Patients with epilepsy who have tried and failed at various forms of treatment must endure a difficult existence. Their standard of living is really poor. Many patients suffer serious injuries, such as burns, fractures, and head traumas, as a result of the extreme rapidity of the seizure attack and the confusion, unconsciousness, and loss of motor control that some types of seizures are accompanied by. These injuries greatly impact the risk associated with epilepsy [4]. Figures 1 and 2, respectively, display epileptic facts and epilepsy statistics.

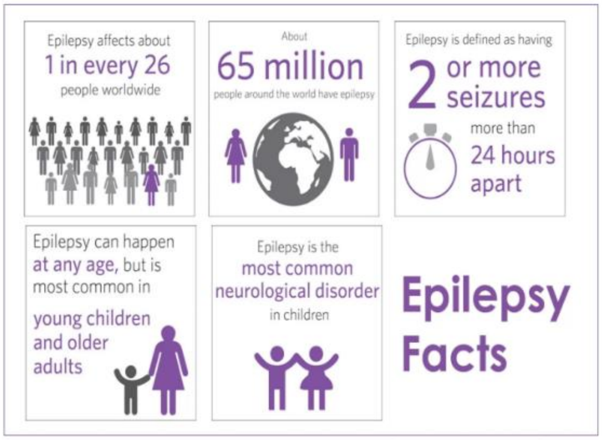

Fig. 1 Epilepsy Facts [25]

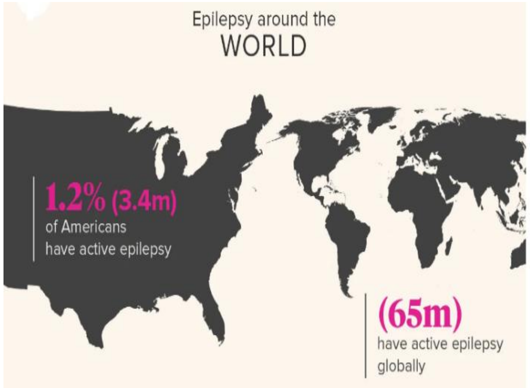

Fig. 2 Epilepsy statastics[25]
Note:3.4m=3.4 million and 65m=65millions

1.2. Seizures and Epilepsy

1.2.1. Seizures

A seizure describes "a transient, momentary change in the electrical activity of the brain" and can cause issues with speech, eye movement, muscular coordination, and behavior.

1.2.2. Epilepsy

Epilepsy is a neurological disorder marked by frequent seizures, consciousness loss with or without movements, and electrical impulses in brain activity. It is believed to be the outward sign of an overabundance and abnormal release of a particular subset of nerve cells [5]. During a seizure, sudden and uncontrolled nerve-cell discharges in the brain result in aberrant bodily functions, often leading to unconsciousness, uncontrollably contracted muscles, or abnormal sensations. [6]. Although seizures are the main sign of epilepsy, they can also be brought on by a variety of other circumstances. Brain electrical abnormalities are the primary cause of epileptic seizures.

A seizure is characterized by a brief period of unusually high or coordinated neuronal activity in the brain. The patient may experience uncontrollable changes in behavior, movement, sensation, or awareness as a result of the rapid breakdown of the brain's neural activity [7-8].

The characteristics that differentiate epilepsy from non-epileptic seizures. Epilepsy is (a) At least one or two unexplained seizures that happen at least 24 hours apart are considered to be epilepsy. (b) One uncontrollable seizure with a high likelihood of more spontaneous seizures; and (c) Recognizing an epileptic condition [9]. Seizures without epilepsy are a response to disturbances beyond the central nervous system, including drinking, abusing drugs, not getting enough sleep, or having a serious disease. According to its genesis, epilepsy might be classified into the following categories

Genetic: probably as a result of genetic disposition.
Structural/metabolic: related to a brain injury.
Unknown: No specific emphasis or syndromes to be found. Unknown causes of epilepsy are currently identified in six out of ten patients, which is regrettable. Over 450,000 adolescents and kids, as well as 2.3 million adults in the US, currently live with epilepsy. Each year, epileptic seizures are identified in about 150,000 people. Every year, 120 people out of every 100,000 in the United States have a newly diagnosed seizure. A seizure will occur in at least 8% of the overall population. Within 5 years, there is a 23 to 80% chance that the first uncontrolled seizure will occur again [10]. In the United States, neurological illnesses have an annual economic cost of around $800 billion. In the US, epilepsy alone brings in about $37 billion annually [11].

Nearly one-sixth of all epilepsy cases worldwide are found in India, and there are projected to be close to 12 million epileptic sufferers. Prevalence was reported to be 3–11/1000 and incidence to be 0.2–0.6/1000 in recent research conducted in India. In developing countries, epilepsy was more prevalent in rural regions than in urban areas [12].

1.3. Analyzing Physiology Signals of Epileptic Seizure

Monitoring several biomedical parameters from the human system, such as (1) electroencephalography, (2) electromyography, (3) electrocardiography, (4) mobility, and (5) an audio message, may help identify epileptic seizures [13, 14]. EEG is the most widely used of these physiological signals due to its benefits, including its (1) high spatial resolution, (2) high temporal resolution, and (3) the ability to capture brain neuronal activity. Traditional EEG measurements can only be carried out in a controlled situation by a trained technician because of their intrusiveness and complicated setup.

Monitoring physiological indicators or other body processes can also help diagnose some seizure types, like generalized onset motor seizures [15,16]. Consequently, in addition to using EEG signals, researchers have developed seizure detection techniques that use a range of non-EEG signals [17]. By separating the methods used to identify seizures into ECG and EEG, we will illustrate about how these recorded signals are employed in the discussion that follows.

1.3.1. Electrocardiogram (ECG)

Electrocardiogram (ECG) monitoring determines the electrical characteristics of the heart, along with the rhythm of the heart and variability in heart rate (HRV). When a person has Generalized Tonic Clonic Seizures (GTCS), their heart rate usually rises. The risk of unexpected unexpected fatalities in epileptics (SUDEP) is thus increased by such events [18]. Furthermore, HRV can be used to detect focal seizures that occur while exercising [19]. When focal onset seizures occur with diminished consciousness, the most typical HRV pattern linked to these seizures is an abrupt, quick acceleration at the start of the seizure [20]. Temporal lobe seizures exhibit a different HRV than psychogenic non-epileptic seizures [21]. An ECG is a useful tool for identifying seizures. Still, there are still many limitations in terms of accuracy and early seizure detection. The ECG signal is portrayed in Figure 3**.**

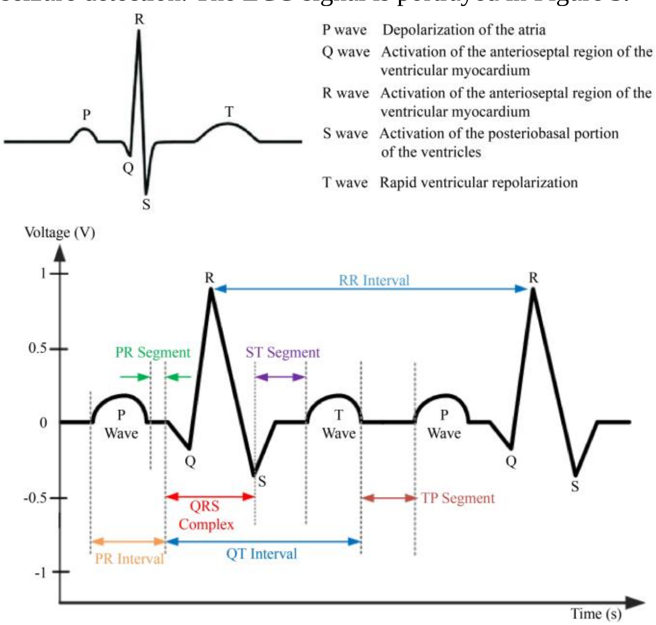

Fig. 3 ECG signal [25]

1.3.2. Electroencephalogram (EEG)

EEG recording is the method most frequently used to collect brain waves for epilepsy. The brain's electrical activity is measured. Due to the abnormal signal patterns that epileptic seizure activity causes on the EEG, we can recognize seizures using fluctuations in the EEG signal.

The paroxysmal aberrant EEG signals depicted in Figure 4. include sharp waves that last 20–70 ms, spikes, and spike-and-slow waves. Slow waves last 200–500 ms after a spike wave [22,23].

With a focus on epileptic seizure detection, we employed both ictal and interictal EEG data, disregarding postictal scenarios, to identify abnormal EEG signals. Whereas ictal action is typified by uninterrupted discharges of polymorphic waves with fluctuating frequency and amplitude, inter-ictal activity's EEG signature is characterized by sporadic transient waveforms [24]. Figure 4 shows the EEG signals.

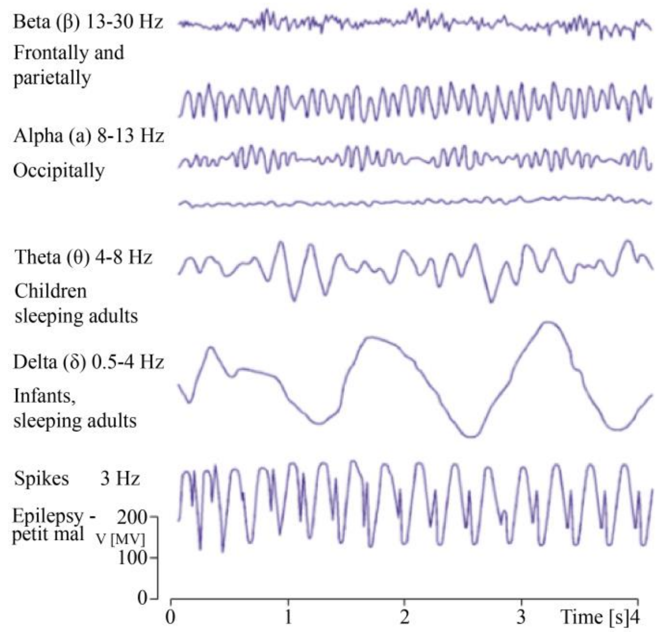

Fig. 4 EEG Signal [25]

A potentially less invasive way of recording EEG signals than with conventional EEG procedures is this promising development. Recording EEG signals close to the ear is a promising development that may lessen the intrusiveness of traditional EEG procedures. While the amplitude of the evoked responses from traditional scalp EEG recordings is generally 10–20 dB higher, their Signal—Noise Ratio (SNR) is often compared [26]. Mikkelsen et al. examined 12 traditional ear electrodes and 32 common scalp electrodes. Similar brain activity is represented by the data collected from the hearing electrodes as by adjacent scalp electrodes [27]. Cleeren et al. used the unilaterally and cross-head bands of the behind-the-ear EEG. In terms of frequency content and temporal waveform, behind-the-ear EEG recordings made during seizures were similar to scalp recordings. Coherence was observed between the scalp EEG channels of twelve patients and the best-matching behind-the-ear EEG channels [28]. According to McLean et al., ambulatory EEG data in epilepsy showed abrupt death; the EEG went flat as soon as the seizure activity stopped. According to the EEG variations graph, some EEG channels may have significant patterns that can be used to identify seizures [29]. The paper is divided into six sections: Section 2 discusses relevant work, and Section 3 presents the materials and procedures for the proposed methodology. Section 4 presents the results, Section 5 analyzes the conclusions, and Section 6 provides a summary of the work.

2. Background

Epileptic seizures can be recognized using a variety of signal-processing techniques and transformations. They are the time domain, frequency domain, and wavelet domain (time-frequency). The time domain is the basis of threshold-based methods. In the frequency domain, the Fast Fourier Transform (FFT), techniques for estimating the power spectrum density, the Minimal Variance Distortionless Response (MVDR) method, and wavelets. There are several temporal and frequency-related restrictions on FFT. The Continuous Wavelet Transform (CWT), which functions in the wavelet domain, is a helpful tool for evaluating the coherence between two signals (CWT). Wavelets are employed for local analysis of the big signal. The wavelet's coefficients display where the signal breaks up. Figure 5 presents a categorization of epilepsy seizure detection techniques.

2.1. Time Domain (or) Threshold-based Methods

The term "time domain" describes how a signal's value changes with time. Time-domain techniques evaluate discrete time and analyze the given epochs (time window), and they are often problem-specific. A healthcare system module developed by IosifMporas et al. in 2007 employs EEG and ECG data as seizure detectors. The module uses support vector machines for classification and short-time evaluation utilizing time-domain and frequency-domain data. Three individuals with absence-diagnosed idiopathic generalized epilepsy served as test subjects for the seizure detection module. For all patients investigated, the obtained seizure detection accuracy was 90% [30]. An automatic method for identifying seizures in the EEG was described by Gotman et al. This method's basis is the breakdown of an EEG into its fundamental waves and the identification of periodic epileptic episodes with a frequency between 3 and 20 c/sec.Simple methods are used to calculate the size of the waves with respect to the background, their length, and their rhythmicity [31]. The technique has been evaluated using 44 samples from intracerebral electrodes and 24 surface recordings, both of which had average recording times of 18.7 hours and 12.4 hours, respectively. A thorough review of the many seizure detection methods was provided by S. Nasehi et al., along with an emphasis on their potential applications in both diagnosis and therapy. EEG and ECG readings are used by many of the algorithms used today to determine the start and end of seizures.

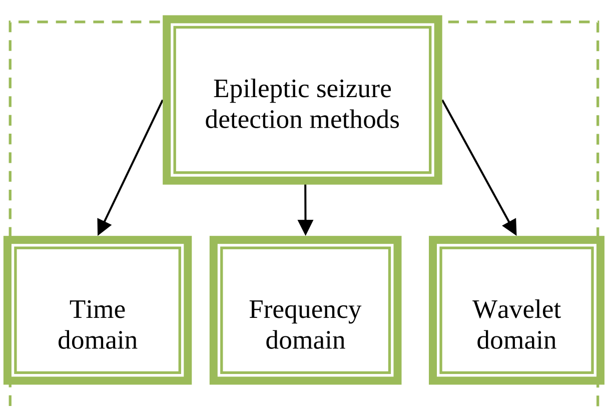

Fig. 5 Classification of Epileptic Seizure detection methods

Until the patients are separated into seizure or non-seizure categories, these methods extract a range of factors from the EEG data alone or in conjunction with the ECG signal. Seizure detectors are categorized into two primary groups: electroencephalography seizure-event detectors and electroencephalography status epilepticus detectors [32]. Electroencephalogram (EEG) signals are acquired using wireless, portable brain monitoring equipment, according to Md. Nazmus Sahad et al. This setup is the basis for the collection of HRV and ECG data. Using the bandpass filter's bandwidth adjusted between 0.5 Hz and 126 Hz, the overall gain has been adjusted to 93.86. The left leg, right leg, left arm, and right arm were all connected to separate inputs.

In settings of elevated cognitive load and a relaxed state, ECG signals and HRV data were collected. Wirelessly transmitting the signals to a distant computer for analysis after they had been digitalized at 256 SPS [33]. MATLAB was used to filter and plot these cardiac signals.

Khan and Shanir presented that the minimum and mean energy values per epoch, as well as the mean energy of all sample points within an epoch, are features for categorization in the suggested method for automated seizure detection. The window size was set at one second. In this case, the classifier is a linear classifier. The CHB-MIT database's algorithm testing involved three subjects, with training and testing using 60% and 40% of the data, respectively. Their average specificity, sensitivity, and detection accuracy were 99.81%, 100%, and 100%, respectively. Based on factors including the mean and median of energy, which have larger values in the seizure epoch compared to the non-seizure epoch, it is easy to discern between seizure and non-seizure epochs [34]. Thomas De et al. claim that the ECG is an electrical signal from the body that can be utilized for automatic home detection online. According to earlier research, tonic-clonic seizures are frequently accompanied by a sharp rise in heart rate. The ictal heart rate characteristics' significant patient-specific behaviour, however, is the fundamental problem that is challenging in creating a patient seizure identification [35].

To identify a channel and identify seizures, Alotaiby et al. presented the multichannel scalp electroencephalogram (EEG) recording histograms. During the training phase, the signal was windowed with a 10-second non-overlapping window, and five histograms were measured from each signal segment. Throughout testing, each section is classified as either ictal or non-ictal using those channel-histogram bins. Following an average moving filter to reduce noise, the sequence is compared to a patient-specific detection threshold. The CHB-MIT dataset, which comprised 26 seizures in 5 individuals, and SEEG of 309.9 Hz were used to test the technique. Their average specificity and sensitivity were determined to be 98.58% and 97.14%, respectively. Asuvaran et al. state that epilepsy is more prevalent in older people and children, A frequently occurring neurological. It is important to distinguish focal seizures from illnesses of the brain, such as epilepsy. Despite the widespread usage of electroencephalograms and electrocardiograms (ECG), the objective of this research is to develop an algorithm that evaluates both EEG and ECG data in order to predict the likelihood of a seizure. The power distributions were calculated in order to identify seizures in the EEG, especially in the delta and theta bands [36].

A hybrid model was presented by Mursalin et al. to determine if an EEG signal contains epilepsy by taking into consideration factors in both the frequency and spatial domains. The frequency domain features are shown together with the assessment of the detruded changes, movement, and the standard deviation and mean of the wavelet coefficients. The findings demonstrate that, in comparison to other contemporary methods and the conventional correlation-based method, the recommended method is more effective at identifying epileptic seizures [37].

Observations: Time-domain techniques are frequently quick and applicable to real-time systems. Frequency-domain analysis, which offers a more in-depth examination of the signal than time-domain analysis, reveals details about the signal's frequency content, overcoming the drawback of time-domain analysis. This frequency domain transform is explained in the next section.

2.2. Frequency Domain

In the time domain approach, the signal is simply analyzed in terms of its amplitude and time components, which is blind to the signal's frequency component. However, if we want to analyze the signal as a whole, the frequency component is equally important. The frequency spectrum of the signal is described in the frequency domain. The advantage of shifting a signal's domain is that it highlights and reveals significant elements of the signal that are not visible upon a visual examination of the initial signal or an undetectable signal in the time domain.

Bhopal proposed the FFT method for identifying epileptic seizures. The neural networks are given the extracted FFT-based characteristics. For their classifiers, they used generalized feed-forward neural network models (GFFNN) and Multi-Layer Perception Networks (MLP). The approach can achieve 100% accuracy, according to the results of the Bonn dataset test [38].

Hills performed an FFT on each one-second-long frame in order to take part in the "U Penn and Mayo Clinic's seizure detection challenge" and gathered magnitudes between 1 and 47 Hz as well as phase data. The feature vector is created using the FFT data and eigenvalues that have been computed in both the time and frequency domains. A random forest classifier with 3000-trees is then used to classify this feature vector [39].

Christine Rosquist et al. described that this illness has always occupied a significant position in biomedicine due to the health risks it presents. Its electroencephalogram can be utilized to make the diagnosis and is characterized by recurrent, unprovoked seizures. EEG measures the brain's electrical activity, and a key component of epilepsy research is the analysis of EEG data to spot epileptic seizures in their early stages.

The machine learning algorithms for pattern recognition that are used to identify epileptic seizures based on EEG were compared. Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) were the two methods that were compared. Although KNN occasionally exhibited somewhat higher reliability, our analysis demonstrates that the two approaches perform similarly [40].

Jing Li et al. analyzed and evaluated the frequency domain properties of electroencephalography (EEG) signal in order to more precisely identify epileptic episodes. On the test EEG signal, the spectrogram and power spectrum were computed using FFT, and the Continuous Wavelet Transform (CWT) was utilized to establish the scalogram. Additionally, two methods, 1 and 2, were tested for their applicability in the detection of epileptic seizures using electrocardiogram (ECG) signals. The third method for identifying irregularities in ECG signals has undergone testing [41].

Darjani, N. et al. calculated epileptic seizure frequency as a feature supplied to k-nearest Neighbor (KNN) to assess the effectiveness of the proposed techniques. With data from neurology and sleep EEG and an accuracy of 99%, the current study was able to tell the difference between pre-ictal and ictal EEG signals [42].

Li, Y. N. et al.showed how to use a hybrid approach based on the Fisher vector technique and multiscale radial basic function to investigate high-resolution time-frequency estimation and evaluate the dynamic behaviour of nonstationary EEG data [43]. Sourabh Banik et al. presented the interaction between EEG and PPG signals during emotional elicitation by audio-visual stimulus, which is analyzed to determine how the brain and heart interact. Using the DEAP database, this investigation discovers that CFC between EEG and PPG signals typically diminishes in the beta and gamma bands as arousal levels increase [44].

Observations: When there is a lot of data to analyze, such as long-term data, frequency domain methods are a good option because they don't need to account for the temporal component of the signal. A mixture of traits from many domains, on the other hand, may lead to extremely positive outcomes. For a more thorough look at the signal, we need a transform that shows both the time and frequency components at the same time. This kind of transformation is explained in the next section.

2.3. Wavelet Domain (Time–Frequency)

In 2016, Hasan et al. presented a novel approach to seizure detection using Hilbert and wavelet transforms. For wavelet and Hilbert transform coefficients, the absolute values of the average, highest, lowest, standard deviation, and average power parameters are obtained separately. The performance was evaluated on the Bonn database, and it was found that applying the Hilbert transform produced some very encouraging results. For the A-E and B-E data sets, accuracy is 100 and 96% in the wavelet case and 100 and 100% in the Hilbert case. Additionally, they have shown that they are 100% sensitive and 100% specific for the Hilbert transform. The algorithm's strength is that it achieves the best accuracy by using only a single decomposition level [45].

In a study by Sharma et al., ten-fold the cross-validation was used on the EEG databases of Bonn University and the Neurology and Sleep Center to test a new approach relying on an Orthogonal Wavelet Filter Bank (OWFB) for the separation of ictal and non-ictal EEG signals. The proposed technique offers a 98% accuracy rate for identifying pre-ictal and ictal brain signals and an accuracy rate of 100% for identifying inter-ictal and ictal EEG signals [46].

The Discrete Cosine Transform (DCT)-based filter bank is proposed to separate EEG signals into five different brain rhythms. The autoregressive moving average and Hurst exponent are produced by these rhythms and supplied into the SVM classifier to carry out the binary recognition of EEG data. Assessment measurements on two publicly accessible EEG datasets are used to evaluate the effectiveness of the current study [47].

In order to accurately diagnose an epileptic episode, Hadiyoso et al. proposed two characteristics: absolute wavelet energy and wavelet entropy. Two features have emerged from the EEG data's division into five bandwidths. The results of the simulation demonstrated that an SVM classifier was able to differentiate between inter-ictal and ictal EEG data with a maximum accuracy of 96% [48].

Andzejak presented various electroencephalography (EEG) states into healthy, rhythmic, and epileptic states. The confusion matrix was used to evaluate the algorithm's sensitivity, specificity, and accuracy. When put to the test on the Bonn database, they were discovered to be 98.33, 100%, and 97.1% respectively. In this situation, Daubechies-4 is the parental wavelet [49].

In order to extract features, Zainuddin et al. developed a set of variables from the wavelet transform of the brain signals based on the standard deviation, maximum, and minimum of the actual values of the wavelet coefficients in each sub-band. After recovery, the features are classified using wavelet neural networks, or WNNs. To evaluate the effectiveness of the suggested method, they investigated several mother wavelets, including the Mexican Hat, Gaussian, and Morlet, for feature extraction using the Bonn database. They found that WNNs with the order 4 Daubechies wavelet and the Morlet wavelet activation function performed best [50].

Two characteristics, relative wavelet energy and wavelet entropy, were proposed by Abbasi et al., who reported the precise detection of an epileptic episode. The EEG data is separated into five frequency bands for examination, and two characteristics have been extracted from each band. The simulation result revealed the greatest classification accuracy of 96% for inter-ictal vsictal EEG signals using an SVM classifier [51].

Panda et al. also describe a five-level decomposition method for feature extraction. The characteristics that were retrieved are entropy, energy, and standard deviation. Daubechies (db-2) is the reference wavelet in this case, and SVM is employed as a classifier. The energy feature had the highest accuracy of 91.2% when the results of the various features were compared. 500 EEG epochs are used to detect epileptic episodes for the purpose of testing the algorithm (100 epochs for each event), which were collected from five distinct neural activities, including eye movement, eye-opening and seizure [52].

Neural network classifiers and discrete cosine harmonic wavelet transform-based features were suggested by G. R. Kiranmayi et al. for the detection of epilepsy[53]. An EEG classification model based on machine learning for the identification of epileptic seizures was presented by M. B. Qureshi et al. [54], and H. Peng et al. reported on automatic epileptic seizure identification via stein kernel-based sparse representation[55].M. Sahani et al., suggested employing a decreased deep convolutional layer autoencoder from EEG signals in conjunction with an upgraded kernel random vector for detection of epileptic episodes [56]**.** J. Cao et al. presented epileptic classification using a feature fusion approach based on deep transfer learning[57]; machine learning algorithms were first presented by Andreas Miltiadous et al. for the diagnosis of epilepsy [58].

Observations: The precision of signal processing techniques has been significantly improved by the use of wavelets. According to our findings, seizure detection can be accomplished with a breakdown level of up to 5. When working with wavelets, It's challenging to recommend a particular classifier, but SVM, artificial neural networks, and KNN might be viable choices. There is a lot of use of the Daubechies wavelet, and the outcomes are extremely fascinating. The purpose of this research is to provide a wavelet coherence function that can be used to compare two signals, which not only reveals the frequencies that two signals overlap but also reveals the timing of these frequencies. We suggest a novel method for analyzing the coherence between the circulatory and central nervous systems of epilepsy patients using electrocardiograms and electroencephalograms based on the above-mentioned literature review.

3. Materials and Methodology

Epileptic seizure detection generally consists of three stages: data gathering, preprocessing, and computation of magnitude squared wavelet coherence. This section covers the signal processing procedures required to analyze the physiological signals of epilepsy seizures that have been recorded. The data processing allowed detection and magnitude-squared wavelet coherence to be constructed.

3.1. Steps for Calculation of Magnitude-Squared Wavelet Coherence between EEG and EEG Signals of Seizure Patients

3.1.1. Database

Children's Hospital Boston Database

This research used data acquired from Boston Children's Hospital. ThePhysioBank ATM, a feature of the PhysioNet, contains ECG and EEG recordings from paediatric patients as well as from young people (up to 25 years old) who have seizures. These recordings are used to obtain physiological signals (ECG and EEG) from healthy participants. 22 people's recordings are included in this database (seventeen females, aged 1.5–19, and Five males, aged 3–22). For an ECG signal calculated using 30-second non-overlapping epochs, these signals were gathered with a resolution of 16 bits at a rate of 512 samples per second. These recordings were made with a one-channel ECG and EEG capture utilizing the International 10-20 method [59].

N&C TEC - ECG and EEG Data

The database for this research was collected using "N&C-TEC: ECG and EEG files, "Mendeley Data [60], 16 people's electrocardiogram (ECG) and electroencephalogram (EEG) data was saved in MAT format. Sixteen undergraduate students were willingly recruited for the study; nine of them were men, and seven of them were women. From 19 to 25 years old, they ranged. Four groups were formed, and two cooperative activities, one with and one without noise, were carried out between them. Each subject's baseline EEG and ECG data were captured for three minutes, followed by ten minutes of noise-free collaboration on the second and ten minutes of silence on the third.

ECG Signals

The heart's electrical activity is known as the ECG. In this work, the BIOPAC system and the Einthoven triangle lead were used to capture it at a frequency of 200 hertz and within a bandwidth of 0.1 to 100 Hz.

EEG Signals

The brain's electrical activity is measured by EEG. The recording locations on the MUSE headband were attached using the 10/20 International System, and four EEG channels with a bandwidth of 0.1 to 100 Hz were recorded at 128 Hz. On the EEG, they were TP7, TP8, AF7, and AF8. The source code was created using MATLAB R2022a [60].

3.1.2. Pre-Processing

ECG Signal Preprocessing: Baseline wanders noise and power line interference noises are the two principal noise types found in Electrocardiogram (ECG) data. The low-frequency noise, known as baseline wander noise, has a frequency of 0.5 to 0.6 Hz. With a 0.5 to 0.6 Hz cutoff frequency high-pass filter, it can be removed. A notch filter with a 50 or 60 Hz cutoff frequency can be used to eliminate power line interference noise or noise from the main supply at that frequency [61].

EEG Signal Preprocessing

Blind Source Separation preprocessing (BSS) is employed in EEG signal preprocessing. In order to remove EEG artifacts, a notch filter with a 50 Hz center frequency is used as the first filter on the EEG signal; for obtaining the necessary EEG data for feature extraction, an IR filter between 8 and 25 Hz has been utilized [62].

3.1.3. Modeling of Magnitude-Squared Wavelet Coherence (MSWC)

The magnitude-squared wavelet coherence assessment evaluates the level of coherence in the time-frequency domain between signals x and y. The inputs x and y have to be equal-length, 1-D real-valued signals. The empirical Morlet wavelet is used to determine the coherence. The block diagram and workflow of the recommended magnitude-squared wavelet coherence method are shown in Figures 6 and 7.

Step : 1 A nonstationary ECG signal is converted into an ECG wavelet using the Morlet wavelet.
Step : 2 A nonstationary EEG signal is converted into an EEG wavelet using the Morlet wavelet.
Step : 3 Calculation of wavelet autocorrelation of the ECG wavelet.
Step : 4 Calculation of wavelet autocorrelation of the EEG wavelet.
Step : 5 Calculation of wavelet cross-correlation of ECG and EEG wavelets
Step : 6 Calculation of magnitude-squared wavelet coherence of ECG and EEG wavelets using wavelet autocorrelation of the ECG wavelet, wavelet autocorrelation of the EEG wavelet, and wavelet cross-correlation of ECG and EEG wavelets

Consider X (ECG signal) and Y (EEG signal), two-time series X(n) and Y(n) whose wavelet transforms are $X_n^x(a,b)$ and $Y_n^{*y}(a,b)$,

The wavelet cross-spectrum between$X_n^x(a,b)$ and $Y_n^{*y}(a,b)$ is $M_n^{xy}(a,b)$

$$M_n^{xy}(a,b) = X_n^x(a,b) * Y_n^y(a,b) \qquad (1)$$

The wavelet auto-spectrum between $X_n^x(a,b)$ and $Y_n^{*y}(a,b)$ is $M_n^{xx}(a,b)$

$$M_n^{xx}(a,b) = X_n^x(a,b) * X_n^{*x}(a,b) \quad (2)$$

The wavelet auto-spectrum between $X_n^x(a,b)$ and $Y_n^{*y}(a,b)$ is $M_n^{yy}(a,b)$

$$M_n^{yy}(a,b) = X_n^y(a,b) * Y_n^{*y}(a,b) \quad (3)$$

Calculation of Magnitude-Squared Wavelet Coherence between wavelet transforms of $X_n^x(a,b)$ and $Y_n^{*y}(a,b)$ is

$$W_n^{xy}(a,b) = \frac{M_n^{xy}(a,b)}{\sqrt{M_n^{xx}(a,b)*M_n^{yy}(a,b)}} \quad (4)$$

$$W_n^{xy}(a,b) = \frac{|M_n^{xy}(a,b)|^2}{M_n^{xx}(a,b)*M_n^{yy}(a,b)} \quad (5)$$

3.3. The Block Diagram of Proposed Method for Determination of Magnitude-Squared Wavelet Coherence ECG and EEG Wavelets

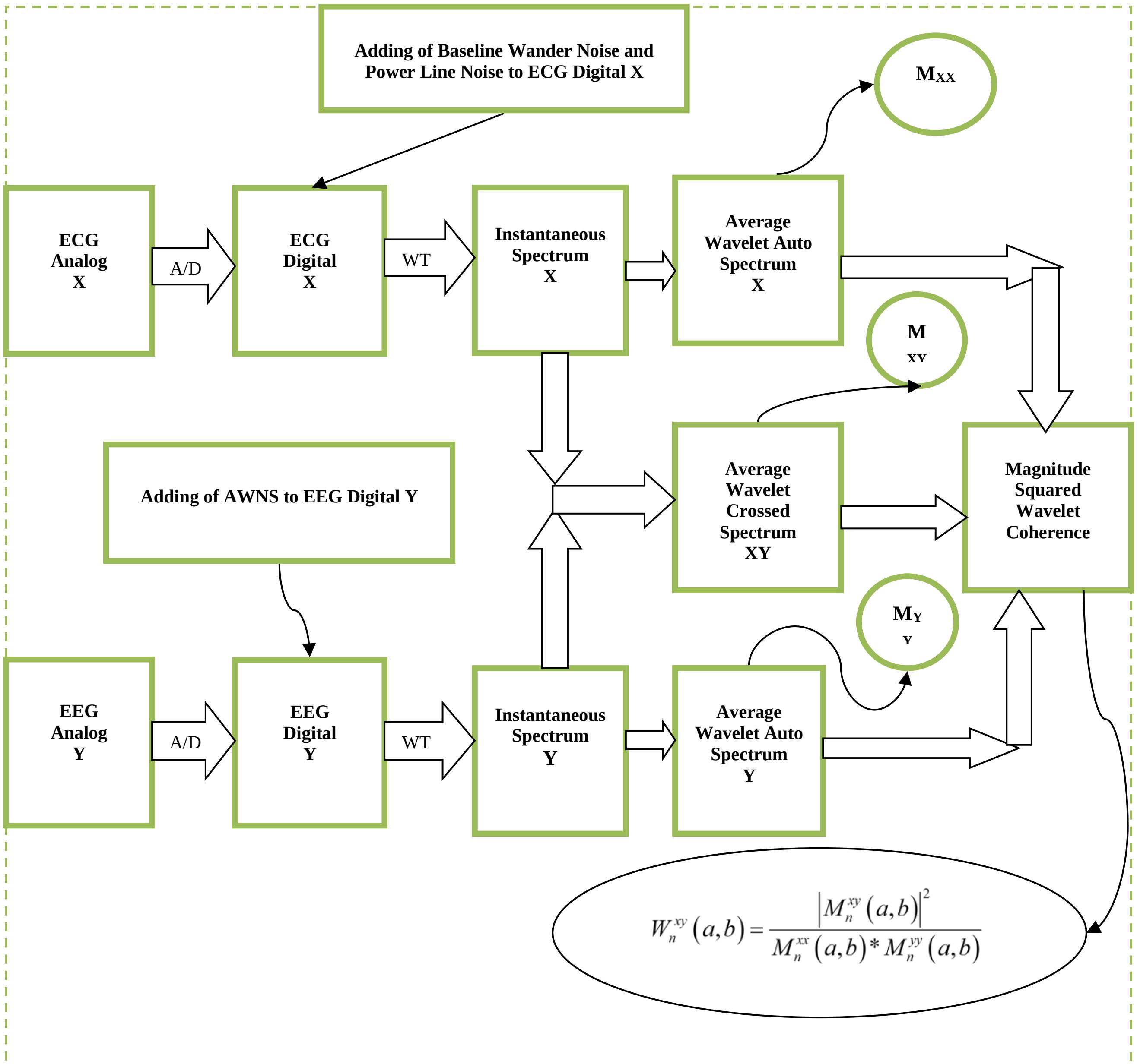

Fig. 6 The Block diagram of MSWC calculation between Electrocardiogram and Electroencephalogram of epilepsy patients

Note: A/D-Analog to Digital Converter, WT-Wavelet Transforms

3.4. The Work Flow of Proposed Method for Determination of Magnitude-Squared Wavelet Coherence ECG and EEG Wavelets

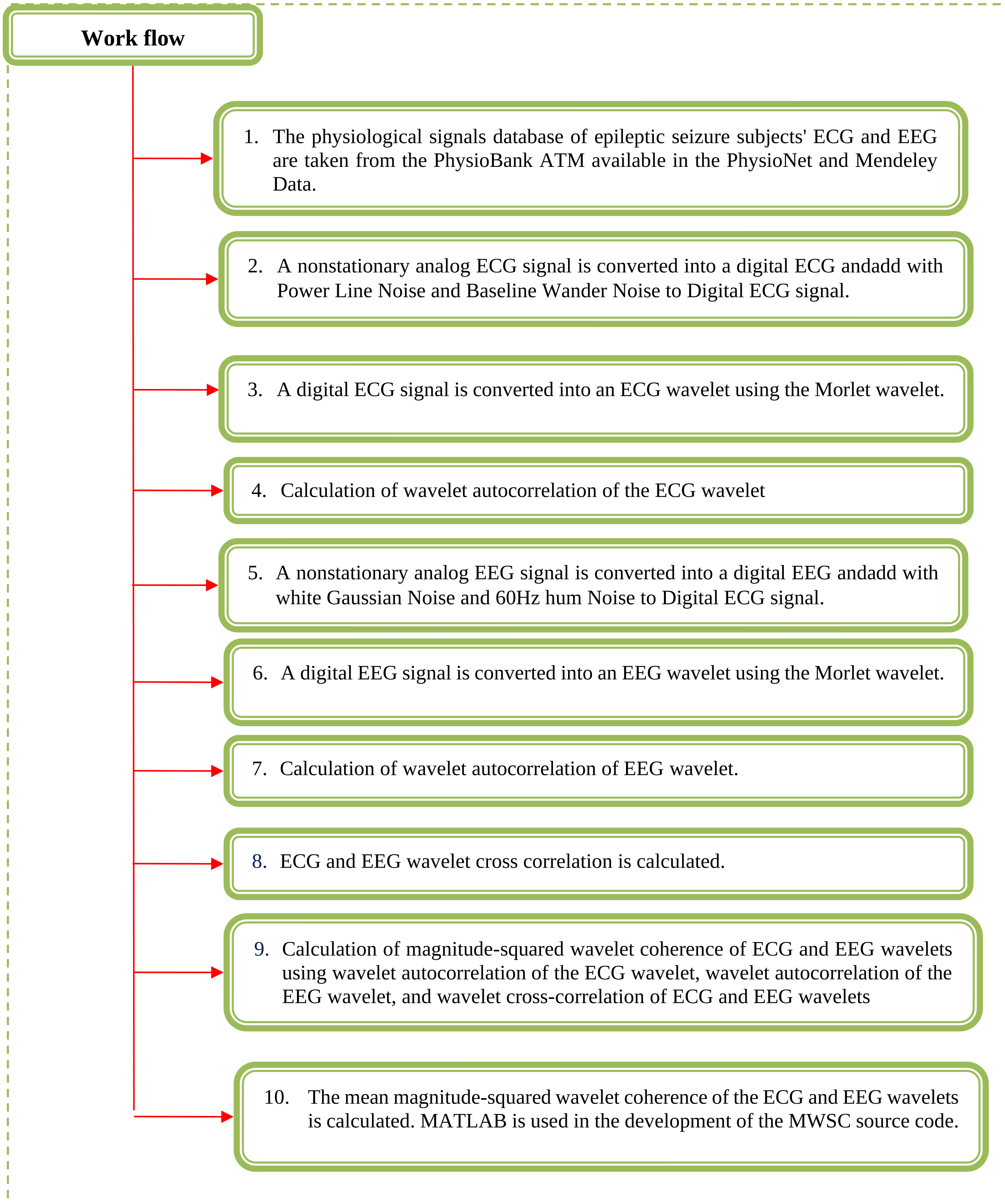

Fig. 7 The Work Flow of Proposed Method for Determination of Magnitude-Squared Wavelet Coherence ECG and EEG Wavelets

4. Results

The data were taken from the physiobank and Mendeley data, 110 epileptic patient samples at a 512-sample/second sampling rate, aged 3 to 25, for investigation and correlation analysis. For the purpose of understanding MSWC four samples are presented here.

4.1. MSWC Analysis

For the MSWC analysis, four samples are chosen at random from a total of 110 samples. An overview of the investigation into the MSWC between the electrocardiogram and corresponding electroencephalogram of epilepsy patients, Figures 8, 9, 11, 12,14,15,17 and18 are depicted, respectively.

Figures 10, 13, 16 and 19 are the variables for the evaluation of MSWC for samples 1, 2, 3 and 4, respectively.

4.1.1. MSWC Analysis for Sample-1

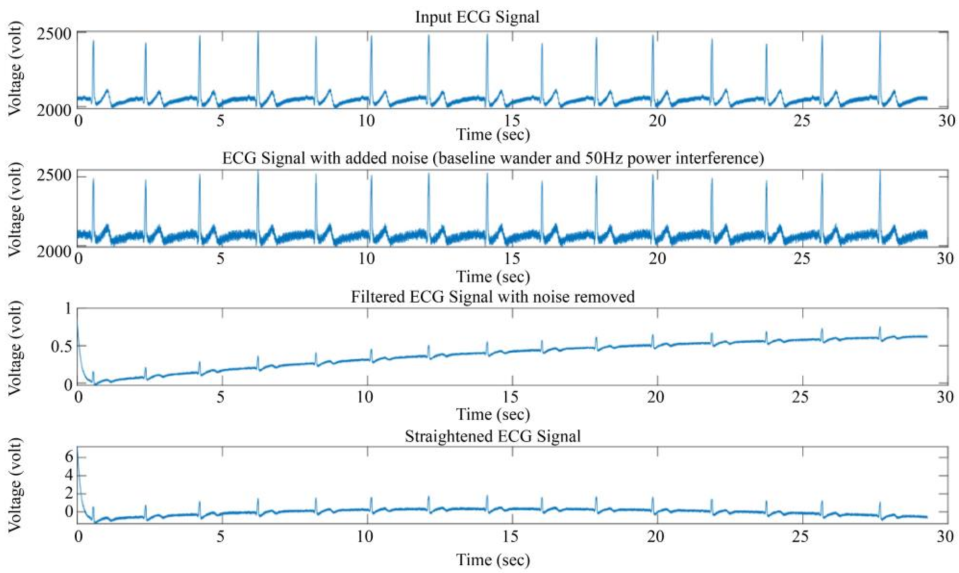

Fig. 8 Input ECG signal for sample-1 is shown in (a) (each signal is sampled for 30 seconds at a sampling rate of 512 samples/second, with a total of 15,360 samples taken). (b) The ECG signal increased in noise (baseline wander and 50 Hz power interference). (c) A noise-free ECG signal that has been filtered, and (d) a straightening ECG signal

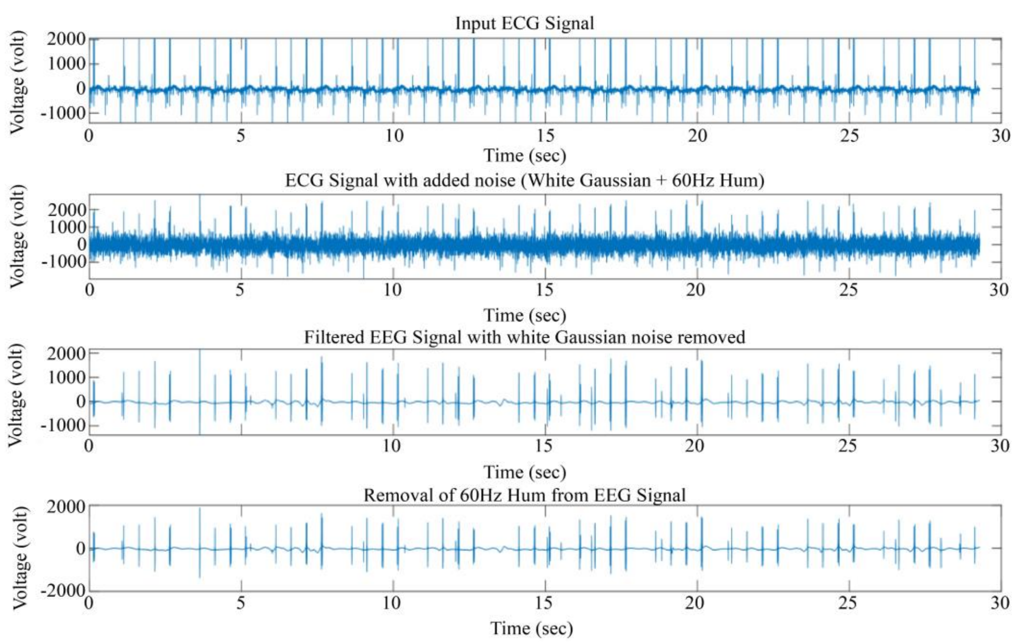

Fig. 9 (a) Input EEG signal for sample- 1 (each signal is sampled for 30 seconds with a sampling rate of 512 samples/second, for a total of 15,360 samples per signal). (b) EEG signal with added noise (white Gaussian plus 60 Hz hum) (c) EEG signal filtered to remove white Gaussian noise (d) Removal of 60 Hz hum from the EEG signal.

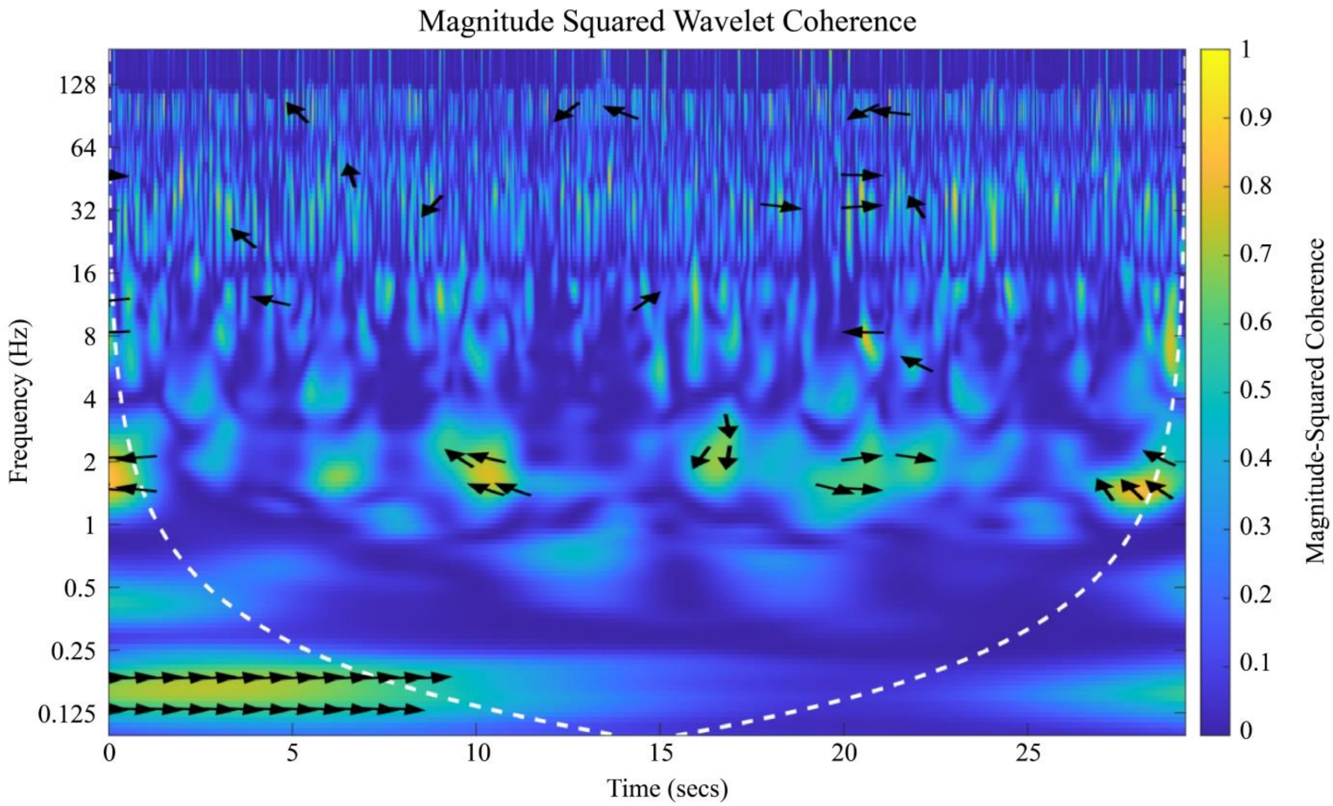

Fig. 10 MSWC between ECG and EEG of sample-1

From Figure 10 it is observed that the average MSC is 0.05, near 0.125 Hz. In addition, two MSC peaks were observed; the average value of MSC is 0.1 in the frequency range from 0.125 Hz to 0.25 Hz, and it was also observed that the highest average value of MSC is 0. Near 1.5-2 Hz, with a bandwidth of 0-128 cycles per second.

4.1.2. MSWC Analysis for Sample-2

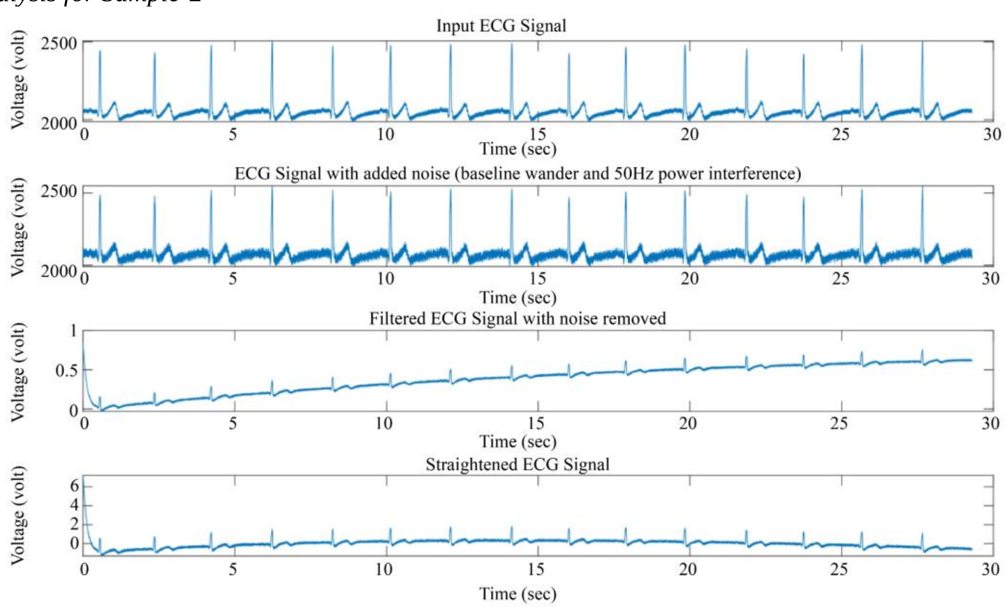

Fig.11 The sample-2 input ECG signal is shown in (a) (each signal is sampled for 30 seconds at a sampling rate of 512 samples/second, with a total of 15,360 samples taken). (b) The ECG signal increased in noise (baseline wander and 50 Hz power interference). (c) A noise-free ECG signal that has been filtered, and (d) a straightening ECG signal.

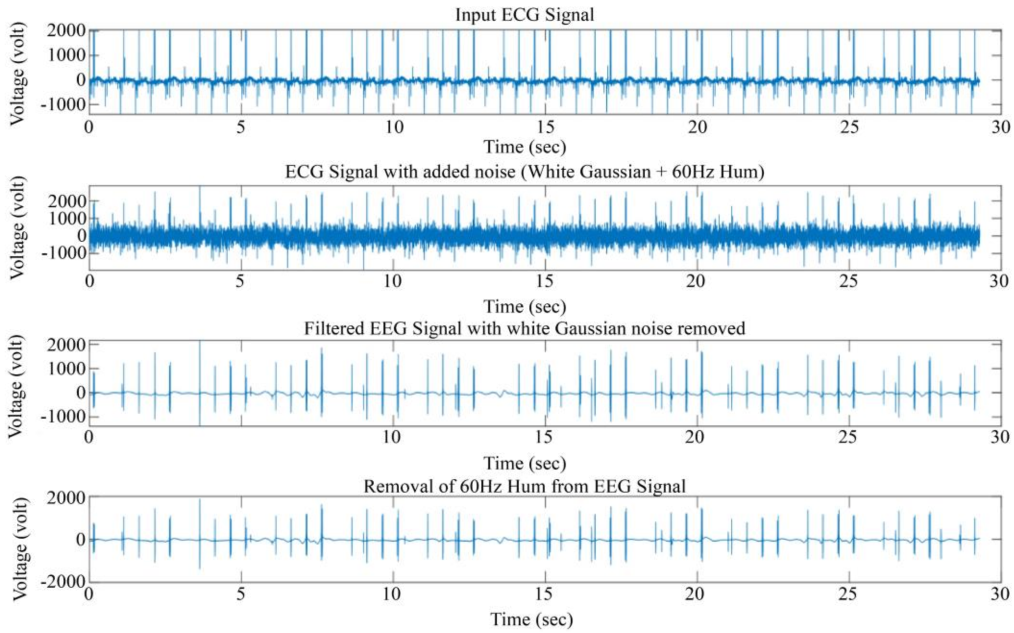

Fig. 12 (a) Input EEG signal for sample- 2 (each signal is sampled for 30 seconds with a sampling rate of 512 samples/second, for a total of 15,360 samples per signal). (b) EEG signal with added noise (white Gaussian plus 60 Hz hum) (c) EEG signal filtered to remove white Gaussian noise (d) Removal of 60 Hz hum from the EEG signal.

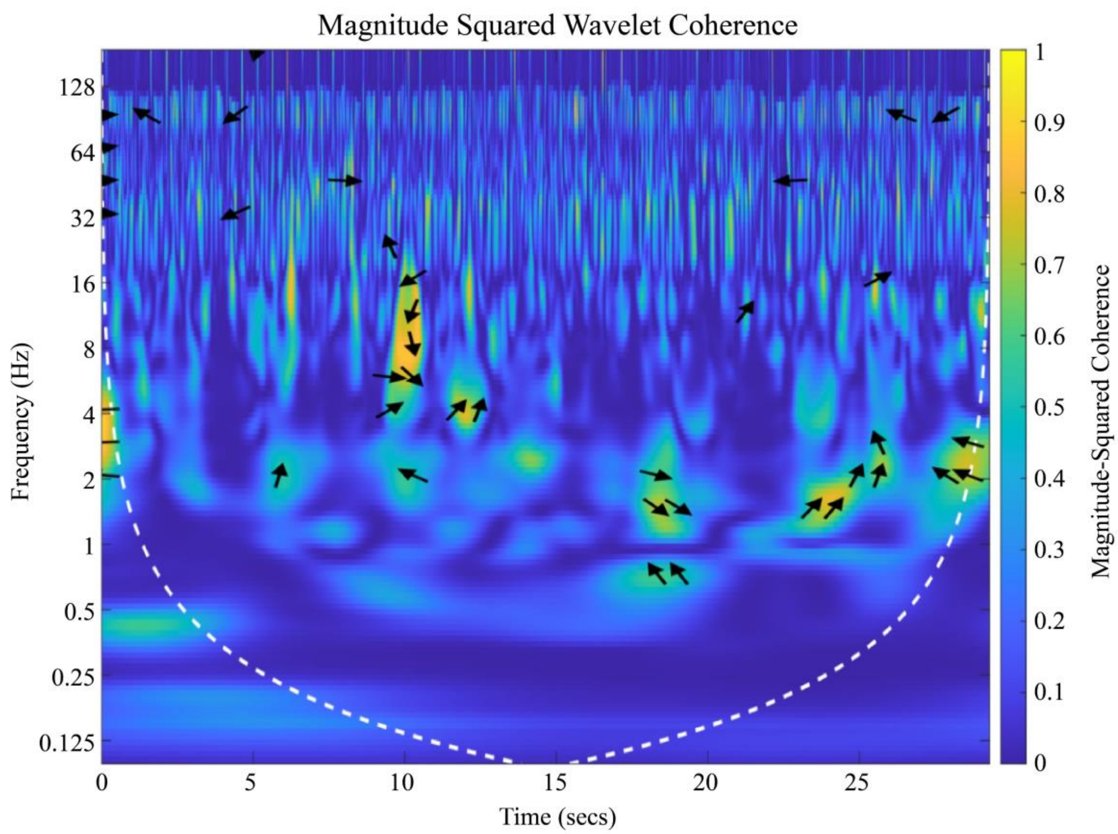

Fig. 13 MSWC between ECG and EEG of sample-2

Figure 13 shows that the mean MSC value is 0.4, which is just around 2 Hz. There is yet one more MSC peak that has been identified; the greatest mean value of MSC is 0.55, or about 6 Hz in the bandwidth of 0-128 cycles/second.

4.1.3. MSWC Analysis for Sample-3

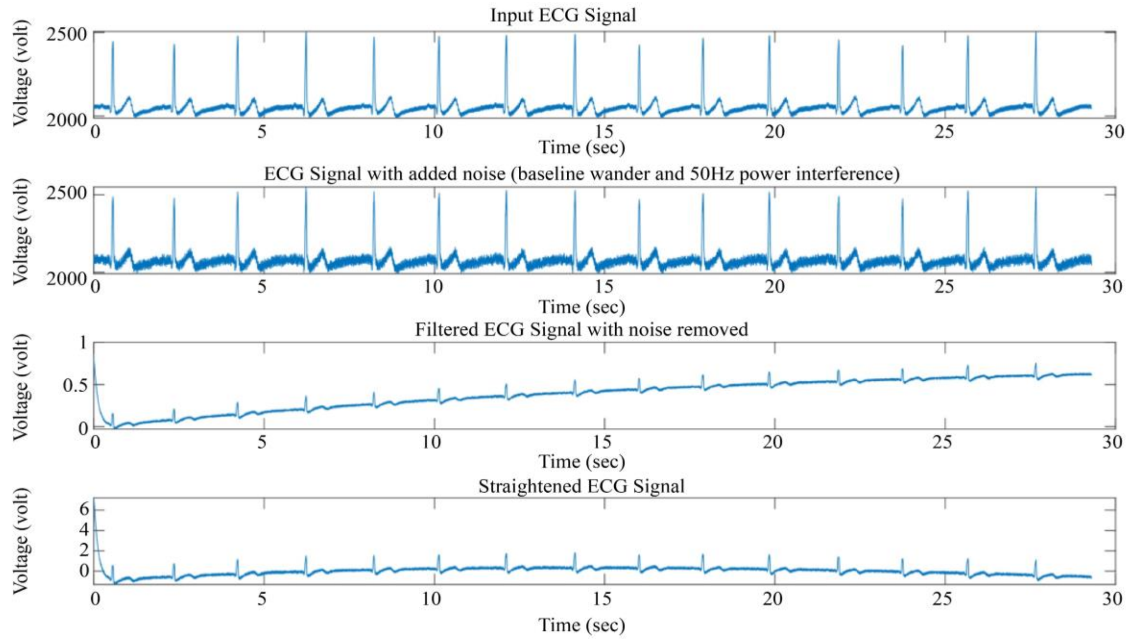

Fig. 14 The sample-3 input ECG signal is shown in (a) (each signal is sampled for 30 seconds at a sampling rate of 512 samples/second, with a total of 15,360 samples taken). (b) The ECG signal increased in noise (baseline wander and 50 Hz power interference). (c) A noise-free ECG signal that has been filtered, and (d) A straightening ECG signal

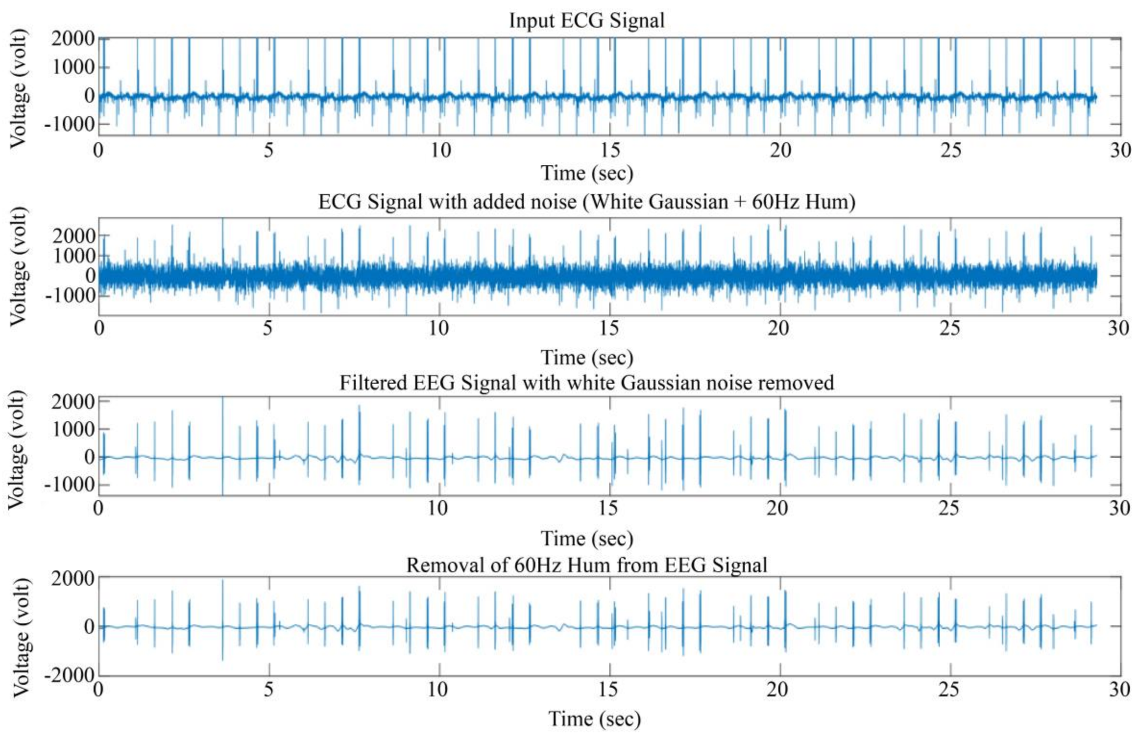

Fig. 15 Input EEG signal for sample- 3 (each signal is sampled for 30 seconds with a sampling rate of 512 samples per second, for a total of 15,360 samples per signal). (b) EEG signal with added noise (white Gaussian plus 60 Hz hum) (c) EEG signal filtered to remove white Gaussian noise (d) Removal of 60 Hz hum from the EEG signal.

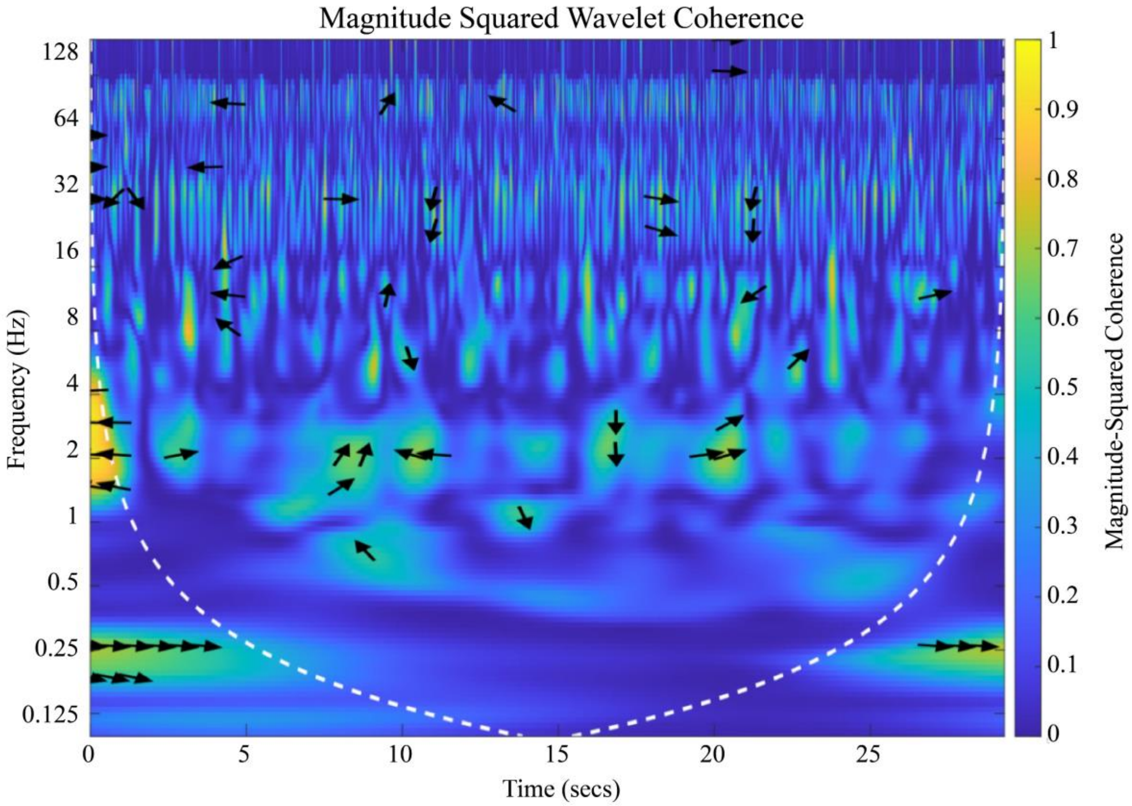

Fig. 16 MSWC between ECG and EEG of sample-3

Figure 16 demonstrates that the highest mean value of MSC is 0.4, which is about equal to the frequency of 2 Hz in the bandwidth of 0-128 cycles/second. The mean value of MSC is 0.15, which is near the frequency of 0.252 Hz, and another MSC peak is observed.

4.1.4. MSWC Analysis for Sample-4

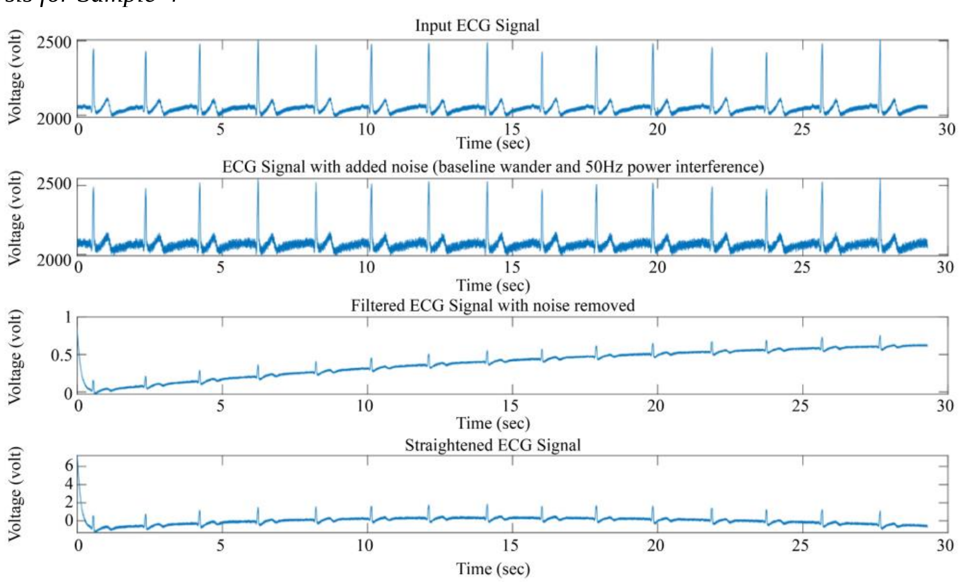

Fig. 17 Input ECG signal for sample-4 is shown in (a) (each signal is sampled for 30 seconds at a sampling rate of 512 samples/second, with a total of 15,360 samples taken). (b) The ECG signal increased in noise (baseline wander and 50 Hz power interference). (c) A noise-free ECG signal that has been filtered, and (d) a straightening ECG signal.

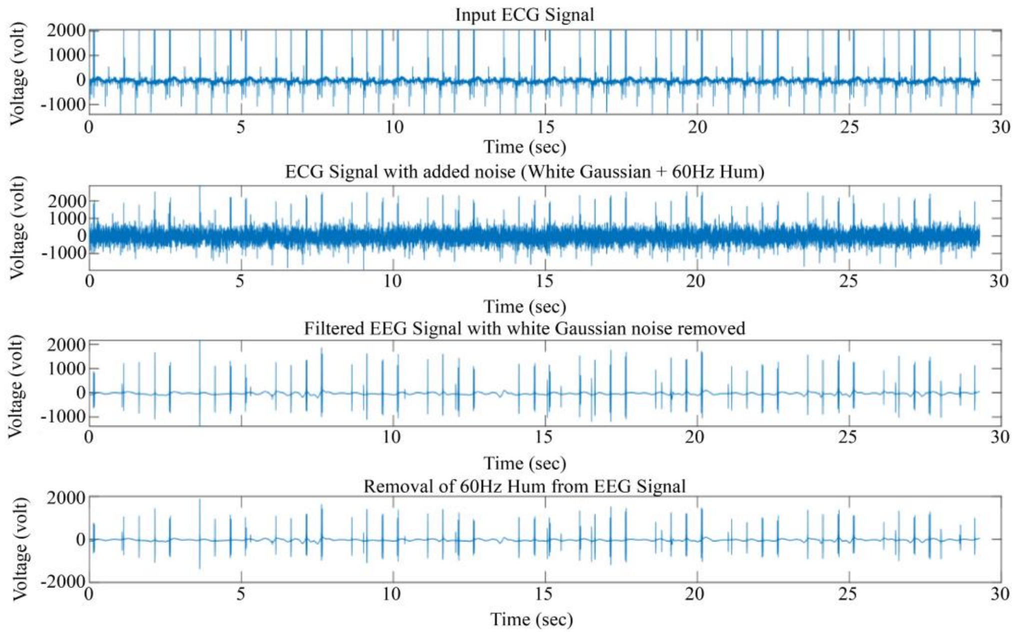

Fig. 18 Input EEG signal for sample- 4 (each signal is sampled for 30 seconds with a sampling rate of 512 samples/second, for a total of 15,360 samples per signal). (b) EEG signal with added noise (white Gaussian plus 60 Hz hum) (c) EEG signal filtered to remove white Gaussian noise (d) Removal of 60 Hz hum from the EEG signal.

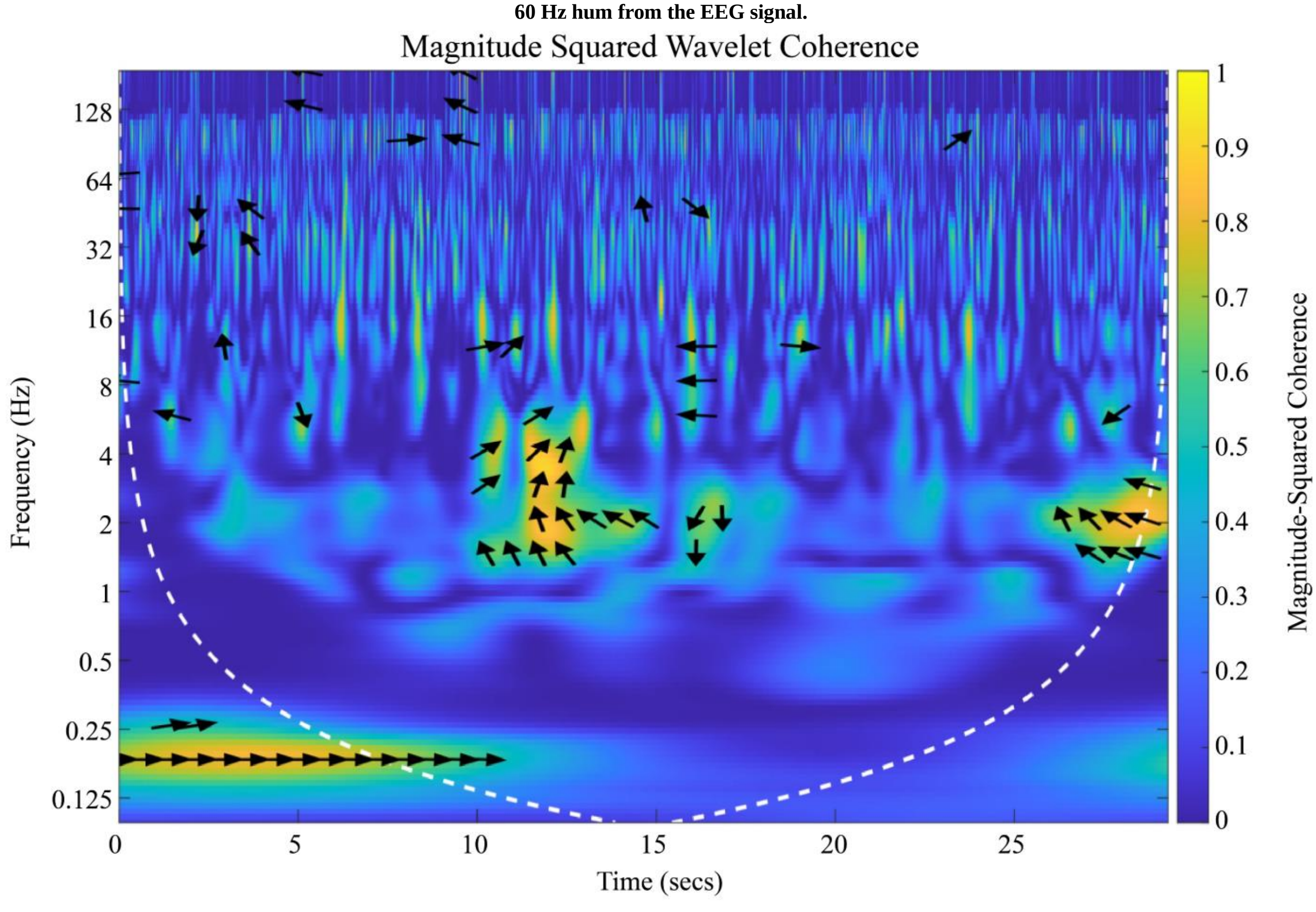

Fig. 19 MSWC between ECG and EEG of sample-4

Fig.19 Bandwidth of 0–128 cycles/second, the mean value of MSC is 0.1, near 0.2 Hz, and two further MSC peaks are found; the mean value of MSC is 0.3, close to 1.5 Hz, and the highest mean value of MSC is 0.4, close to 2 Hz.

5. Discussion

In this proposed method, the main objective of predicting brain-to-heart maximum coherence at an epileptic seizure is achieved, which is in line with the recent methods proposed in the literature. Abbasi et al. discussed improving prediction accuracy and categorizing various EEG signal states into normal, kinetic, and epileptic states in 2017 [51]. The signal is divided into five levels using this method. The fifth low-frequency level was rejected, leaving them with the first four levels for further processing. The highest value, lowest value, median, and standard deviation are among the features derived for each sub-band. MLP neural network multilayer perceptron technology served as the classifier. The Bonn database test method had 98.33% accuracy, 100 percent sensitivity, and 97.1% specificity. The performance was calculated using the confusion matrix. In this case, the mother wavelet is Daubechies-4 [49]. Jing Li et al. evaluated electroencephalography (EEG) signals' frequency domain characteristics in 2018 with the goal of improving the ability to recognize epileptic seizures. Both CWT and FFT were used to analyze the test EEG signal to produce the power spectrum, spectrogram, and scalogram, respectively. Additionally, for the purpose of identifying epileptic seizures, two schemes, namely, procedures 1 and 2, were put into practice. The two methods' suitability for use with Electrocardiogram (ECG) signals was also examined. Tests were conducted using the third technique for detecting anomalies in ECG signals [41]. In 2019, Li, Y. Cui., et al. [43] introduced a hybrid approach for investigating high-resolution time-frequency estimation to examine the dynamic behavior of nonstationary EEG signals. Multiscale radial fundamental functions and the Fisher vector approach form the foundation of this methodology. Dajani, N. et al. evaluated the k-nearest neighbor algorithm and used the seizures with an epileptic density as an element as input to assess the effectiveness of the KNN. In the present work, pre-ictal and ictal EEG signals could be distinguished with 99% accuracy using an EEG dataset from neurology and sleep [41]. Hadiyoso et al. recommended wavelet entropy and relative wavelet energy as two features for the precise identification of an epileptic episode in 2021. The five frequency bands are used to separate the EEG signals into two characteristics. Inter-ictal vs. ictal EEG signals showed the highest classification accuracy, scoring 96%, according to the findings of the simulation employing an SVM classifier [46]. The larger value of the mean MSC indicates the maximum level of coherence between the electroencephalography and electrocardiography data in accordance with the intended research. The lower mean MSC value also suggests a lack of coherence between the electroencephalography and electrocardiography data. MSC values of 0.05, 0.1, and 0.4 between the ECG and EEG signals are found in epileptic seizure sample 1. In the bandwidth of 0 to 512 samples/second, the MSC values are also 0.4 and 0.55 in sample 2 of an epileptic seizure and 0.15 and 0.4 in sample 3 of an epileptic seizure, respectively. The MSC value between the ECG and EEG is smaller than 0.55 on averages in the first, second, third, and fourth samples. In patients with epileptic seizures, the mean of the MSC is determined as the minimum between the ECG signal and the EEG signal.

6. Conclusion

In this paper, the maximum coherence values of epileptic seizures were estimated using the MSWC between the ECG and EEG signals. Children's Hospital Boston's electrocardiogram and electroencephalogram signals are obtained using PhysioNet and Mendeley data from "N&C-TEC: ECG and EEG files ".110 samples from the epileptic seizure are considered in the analysis. The mean MSC value between the electrocardiogram and electroencephalogram was determined for the first sample, the second sample, the third sample, and the fourth sample, which were selected from the 38 unhealthy samples for validation. For the four samples, the MSC mean of the electrocardiogram and electroencephalography signals were found to be very low (less than 0.55). It shows that the coherence value between the cardiovascular system and the central neurological system—i.e., the coherence between the heart and the brain is decreased in epileptic seizure patients. The assessment of anomalies in the brain and heart is more useful for the proposed method of magnitude squared coherence estimation. The future scope of our experimental research is more useful for early identification and diagnosis of heart and brain problems.

Acknowledgement

The authors are profoundly thankful to Vellore Institute of Technology, Vellore, Tamil Nadu, India and V.R. Siddhartha Engineering College, Vijayawada, Andhra Pradesh, India, for their encouragement.

References

[1] Epilepsy, World Health Organization, 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/epilepsy

[2] Mary Jane England et al., "Epilepsy Across the Spectrum: Promoting Health and Understanding-A Summary of the Institute of Medicine Report," *Epilepsy & Behavior*, vol. 25, no. 2, pp. 266-276, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[3] Ashok Sharmila, and Purusothaman Geethanjali, "A Review on the Pattern Detection Methods for Epilepsy Seizure Detection from EEG Signals," *Biomedical Engineering*, vol. 64, no. 5, pp. 507-517, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[4] Turky N. Alotaiby et al., "Channel Selection and Seizure Detection using a Statistical Approach," *2016 5th International Conference on Electronic Devices, Systems and Applications (ICEDSA)*, Ras Al Khaimah, United Arab Emirates, pp. 1-4, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[5] Rashmi Anupozu, and Rama Bobba, "Epilepsy – A Comprehensive Review," *International Journal of Pharma Research*, vol. 8, no. 11, pp. 375-391, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[6] P.A. Dekker, "Epilepsy: A Manual for Medical and Clinical Officers," *World Health Organization*, pp. 1-124, 2002. [Google Scholar] [Publisher Link]
[7] Andrea Varsavsky, Iven Mareels, and Mark Cook, *Epileptic Seizures and the EEG, Measurement, Models, Detection, and Prediction*, CRC Press, pp. 1-370, 2010. [CrossRef] [Google Scholar] [Publisher Link]
[8] Jerome Engel, *Seizures and Epilepsy*, Oxford University Press, pp. 1-706, 2013. [Google Scholar] [Publisher Link]
[9] Zulfi Haneefand, and Atul Maheshwari, *A Concise Manual of Epilepsy*, Createspace Independent Publishing, pp. 1-182, 2016. [Publisher Link]
[10] Hirak Kumar Mukhopadhyay et al., "Epilepsy and Its Management: A Review," *Journal of Pharma Science Technology*, vol. 1, no. 2, pp. 20-26, 2012. [Google Scholar]
[11] Hae Won Shin et al., "Review of Epilepsy - Etiology, Diagnostic Evaluation and Treatment," *International Journal of Neurorehabilitation*, vol. 1, no. 3, 2014. [CrossRef] [Google Scholar] [Publisher Link]
[12] Senthil Amudhan, Gopalkrishna Gururaj, and Parthasarathy Satishchandra, "Epilepsy in India, I: Epidemiology in Public Health," *Annals of Indian Academy of Neurology*, vol. 18, no. 3, pp. 263–277, 2015. [CrossRef] [Google Scholar] [Publisher Link]
[13] Anouk Van de Vel et al., "Non-EEG Seizure Detection Systems and Potential SUDEP Prevention: State of the Art," *Seizure*, vol. 22, no. 5, pp. 345–355, 2013. [CrossRef] [Google Scholar] [Publisher Link]
[14] Sriram Ramgopal et al., "Seizure Detection, Seizure Prediction, and Closed Loop Warning Systems in Epilepsy," *Epilepsy and Behavior*, vol. 37, pp. 291-307, 2014. [CrossRef] [Google Scholar] [Publisher Link]
[15] Sigge N. Larsen et al., "Detection of Tonic Epileptic Seizures Based on Surface Electromyography," *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, IL, USA, pp. 942-945, 2014. [CrossRef] [Google Scholar] [Publisher Link]
[16] Tamara M. Nijsen et al., "Automated Detection of Tonic Seizures using 3-D Accelerometry," *4th Europe an Conference of the International Federation for Medical and Biological Engineering*, Antwerp, Belgium, pp. 188-191, 2009. [CrossRef] [Google Scholar] [Publisher Link]
[17] Diana Cogan et al., "Multi-bio Signal Analysis for Epileptic Seizure Monitoring," *International Journal of Neural Systems*, vol. 27, no.1, 2017. [CrossRef] [Google Scholar] [Publisher Link]
[18] L.D. Blumhardt, P.E.M. Smith, and Lynne Owen, "Electrocardiographic Accompaniments of Temporal Lobe Epileptic Seizures," *Lancet Journal*, vol. 327, no. 8489, pp. 1051-1056, 1986. [CrossRef] [Google Scholar] [Publisher Link]
[19] Jesper Jeppesen et al., "Seizure Detection based on Heart Rate Variability using a Wearable Electrocardiography Device," *Epilepsia*, vol. 60, no. 10, pp. 2105-2113, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[20] P.E.M. Smith et al., "Profiles of Instant Heart Rate during Partial Seizures," *Electroencephalography and Clinical Neurophysiology*, vol. 72, no. 3, pp. 207-217, 1989. [CrossRef] [Google Scholar] [Publisher Link]
[21] Athi Ponnusamy, Jefferson L.B. Marques, and Markus Reuber, "Comparison of Heart Rate Variability Parameters during Complex Partial Seizures and Psychogenic Nonepileptic Seizures," *Epilepsia*, vol. 53, no. 8, pp. 1314-1321, 2012. [CrossRef] [Google Scholar] [Publisher Link]
[22] Yuedong Song, "A Review of Developments of EEG-Based Automatic Medical Support Systems for Epilepsy Diagnosis and Seizure Detection," *Journal of Biomedical Science and Engineering*, vol. 4, pp. 788-796, 2011. [Google Scholar] [Publisher Link]
[23] Alexandros T. Tzallas et al., "Automated Epileptic Seizure Detection Methods: A Review Study," *Epilepsy-Histological, Electroencephalographic and Psychological Aspects*, pp. 75-98, 2012. [CrossRef] [Google Scholar] [Publisher Link]
[24] Ramendra Nath Bairagi, "Epileptic Seizure Identification in EEG Signals using DWT, ANN and Sequential Window Algorithm," *Soft Computing Letters*, vol. 3, pp. 1-10, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[25] WorldPress Without Limits. [Online]. Available: https://wordpress.com/
[26] P. Kidmose, D. Looney, and D.P. Mandic, "Auditory Evoked Responses from Ear-EEG Recordings," *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Diego, CA, USA, 2012. [CrossRef] [Google Scholar] [Publisher Link]
[27] Kaare B. Mikkelsen et al., "EEG Recorded from the Ear: Characterizing the Ear-EEG Method," *Neuroscience*, vol. 9, pp. 1-8, 2015. [CrossRef] [Google Scholar] [Publisher Link]
[28] Evy Cleeren et al., "Comparison between Scalp EEG and Behind-the-Ear EEG for Development of a Wearable Seizure Detection System for Patients with Focal Epilepsy," *Sensors*, vol. 18, no. 1, 2018. [CrossRef] [Google Scholar] [Publisher Link]
[29] S.S. Papacostas, "Sudden Unexpected Death in Epilepsy: Experience from a Tertiary Epilepsy Centre in Cyprus with Review of the Literature," *Hippokratia*, vol. 19, no. 4, pp. 338-343, 2015. [Google Scholar] [Publisher Link]
[30] Iosif Mporas et al., "Seizure Detection using EEG and ECG Signals for Computer-based Monitoring, Analysis and Management of Epileptic Patients," *Expert Systems with Applications*, vol. 42, no. 6, pp. 3227-3233, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[31] J. Gotman, "Automatic Recognition of Epileptic Seizures in the EEG," *Electroencephalography and Clinical Neurophysiology*, vol. 54, no. 5, pp. 530-540, 1982. [CrossRef] [Google Scholar] [Publisher Link]

[32] S. Nasehi, and H. Pourghassem, "Seizure Detection Algorithms Based on Analysis of EEG and ECG Signals: A Survey," *Neurophysiology*, vol. 44, pp. 174-186, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[33] Md. Nazmus Sahadat, S. Consul-Pacareu, and Bashir I. Morshed, "Wireless Ambulatory ECG Signal Capture for HRV and Cognitive Load Study using the Neuro Monitor Platform," *2013 6th Annual International IEEE EMBS Conference on Neural Engineering (NER)*, San Diego, CA, USA, pp. 497-500, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[34] E. Tessy, P.P. Muhammed Shanir, and Shaleena Manafuddin, "Time Domain Analysis of Epileptic EEG for Seizure Detection," *2016 International Conference on Next Generation Intelligent Systems (ICNGIS)*, Kottayam, India, pp. 1-4, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[35] Thomas De Cooman et al., "Online Detection of Tonic-Clonic Seizures in Pediatric Patients using ECG and Low-Complexity Incremental Novelty Detection," *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Milan, Italy, pp. 5597-5600, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[36] A. Asuvaran, and G. Elatharasan, "Analysis of ECG and EEG Signals to Detect Epileptic Seizures," *International Journal of Engineering Research & Technology (IJERT)*, vol. 4, no. 24, pp. 1-4, 2018. [CrossRef] [Publisher Link]

[37] Md Mursalina et al., "Automated Epileptic Seizure Detection using Improved Correlation-based Feature Selection with Random Forest Classifier," *Neurocomputing*, vol. 241, pp. 204-214, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[38] Ashwini D. Bhople, and P.A. Tijare, "Fast Fourier Transform based Classification of Epileptic Seizure using Artificial Neural Network," *International Journal of Advanced Research Computer Science Software Engineering*, vol. 2, no. 4, 2012. [Google Scholar]

[39] Narendra Kumar Ambulkar, and S.N. Sharma, "Detection of Epileptic Seizure in EEG Signals using Window Width Optimized S-Transform and Artificial Neural Networks," *2015 IEEE Bombay Section Symposium (IBSS)*, Mumbai, India, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[40] Maeike Zijlmans, Danny Flanagan, and Jean Gotman, "Heart Rate Changes and ECG Abnormalities during Epileptic Seizures: Prevalence and Definition of an Objective Clinical Sign," *Epilepsia*, vol. 43, no. 8, pp. 847-854, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[41] Jing Li, "*Digital Signal Characterization for Seizure Detection using Frequency Domain Analysis*," Student thesis, School of Electrical Engineering and Computer Science, pp. 1-63, 2021. [Google Scholar] [Publisher Link]

[42] Nastaran Darjani, and Hesam Omranpour, "Phase Space Elliptic Density Feature for Epileptic EEG Signals Classification using Metaheuristic Optimization Method," *Knowledge-Based Systems*, vol. 205, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[43] Yang Li et al., "Epileptic Seizure Detection in EEG Signals using Sparse Multiscale Radial Basis Function Networks and the Fisher Vector Approach," *Knowledge-Based Systems*, vol. 164, pp. 96-106, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[44] Sourabh Banik et al., "Assessment of EEG-PPG Cross Frequency Coherence under Evoked Emotional Arousal," *Current Directions in Biomedical Engineering*, vol. 10, no. 4, pp. 49-52, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[45] Hasan Polat, and Mehmet Sirac Ozerdem, "Epileptic Seizure Detection from EEG Signals by Using Wavelet and Hilbert Transform," *2016 XII International Conference on Perspective Technologies and Methods in MEMS Design (MEMSTECH)*, Lviv, Ukraine, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[46] Manish Sharma, Ankit A. Bhurane, and U. Rajendra Acharya, "MMSFL-OWFA: A Novel Class of Orthogonal Wavelet Filters for Epileptic Seizure Detection," *Knowledge-Based Systems*, vol. 160, pp. 265-277, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[47] Anubha Gupta, Pushpendra Singh, and Mandar Karlekar, "A Novel Signal Modeling Approach for Classification of Seizure and Seizure-free EEG Signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 5, pp. 925-935, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[48] S. Hadiyoso, I.D. Irawati, and A. Rizal, "Epileptic Electroencephalogram Classification using Relative Wavelet Sub-band Energy and Wavelet Entropy," *International Journal of Engineering*, vol. 34, no. 1, pp. 75-81, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[49] R.G. Andrzejak, The Bonn EEG Time Series Download Page. [Online]. Available: https://www.upf.edu/web/ntsa/downloads/-/asset_publisher/xvT6E4pczrBw/content/2001-indications-of-nonlinear-deterministic-and-finite-dimensional-structures-in-time-series-of-brain-electrical-activity-dependence-on-recording-regi?inheritRedirect=false&redir

[50] Zarita Zainuddin, Lai Kee Huong, and Ong Pauline, "On the use of Wavelet Neural Networks in the Task of Epileptic Seizure Detection from Electroencephalography Signals," *Procedia Computer Science*, vol. 11, pp. 149-159, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[51] Rezvan Abbasi, and Mansour Esmaeilpour, "Selecting Statistical Characteristics of Brain Signals to Detect Epileptic Seizures using Discrete Wavelet Transform and Perceptron Neural Network," *International Journal of Interactive Multimedia Artificial Intellegence*, vol. 4, no. 5, pp. 33-38, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[52] R. Panda et al., "Classification of EEG signal using Wavelet Transform and Support Vector Machine for Epileptic Seizure Diction," *International Conference on Systems in Medicine and Biology*, Kharagpur, India, pp. 405-408, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[53] G.R. Kiranmayi, and V. Udayashankara, “Detection of Epilepsy using Discrete Cosine Harmonic Wavelet Transform-based Features and Neural Network Classifier,” *International Journal of Biomedical Engineering and Technology*, vol. 32, no. 2, pp. 109-122, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[54] Muhammad Bilal Qureshi et al., “Machine Learning-based EEG Signals Classification Model for Epileptic Seizure Detection,” *Multimedia Tools and Applications*, vol. 80, pp. 17849-17877, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[55] Hong Peng et al., “Automatic Epileptic Seizure Detection Via Stein Kernel-based Sparse Representation,” *Computers in Biology and Medicine*, vol. 132, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[56] Mrutyunjaya Sahani, Susanta Kumar Rout, and Pradipta Kishor Dash, “Epileptic Seizure Recognition using Reduced Deep Convolutional Stack Autoencoder and Improved Kernel RVFLN from EEG Signals,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 15, no. 3, pp. 595-605, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[57] Jiuwen Cao et al., “Epileptic Classification with Deep-transfer-learning-based Feature Fusion Algorithm,” *IEEE Transactions on Cognitive and Developmental Systems*, vol. 14, no. 2, pp. 684-695, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[58] Andreas Miltiadous et al., “Machine Learning Algorithms for Epilepsy Detection based on Published EEG Databases: A Systematic Review,” *IEEE Access*, vol. 11, pp. 564-594, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[59] Ary L. Goldberger et al., “Physiobank, Physiotoolkit, and Physionet Components of a New Research Resource for Complex Physiologic Signals,” *Circulation*, vol. 101, no. 23, pp. 1-6, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[60] Magdalena Damian Chavez et al., “N&C-TEC: ECG and EEG Files,” *Mendeley Data*, 2020. [CrossRef] [Publisher Link]

[61] R2024b Release Highlights – MATLAB and Simulink. [Online]. Available: https://in.mathworks.com/products/new_products/latest_features.html

[62] Rahul Kher, “Signal Processing Techniques for Removing Noise from ECG Signals,” *Journal of Biomedical Engineering and Research*, vol. 3, 2019. [Google Scholar]