Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Artificial Intelligence Powered System for Epilepsy Detection Using EEG Biomarkers

Ali Al-nuaimi [1, *], and Shaymaa Al-juboori [2]
[1] *College of Education for Pure Science (Ibn Al-Haitham), University of Baghdad, Al Adhamiya, Baghdad 10053, Iraq*
[2] *School of Engineering, Computing and Mathematics, Faculty of Science and Engineering, University of Plymouth, Drake Circus, Plymouth PL4 8AA, UK*
**Correspondence: ali.h.h@ihcoedu.uobaghdad.edu.iq*

ARTICLE INFO

Received: 30 Dec 2024

Revised: 15 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

One of the most prevalent neurological disorders is epilepsy. Epileptic seizures can occur repeatedly in people with the condition for no recognisable reason. The diagnostic methods dependent on EEG are promising. EEG has uncovered the dynamic functioning of all brain areas throughout time. Its low cost, non-invasiveness, and simply make it crucial for clinical evaluations of brain function. Integrating multiple EEG biomarkers as a compound biomarker could provide a high performance that may accelerate the diagnosis speeds. Artificial intelligence techniques such as machine learning and deep learning provide a significant result in healthcare applications. Logistic Regression (LR), Naive Bayes (NB), and Neural Network (NN) were evaluated using a compound biomarker containing eleven EEG features that were extracted from the Bonn EEG dataset. The aim of this study is to evaluate the feasibility of integrating multiple EEG biomarkers as compound biomarkers for identifying epileptic people. The outcomes showed the performance of all LR, NB, and NN detection models provide a high performance with sensitivity and specificity of greater than 90%.

Keywords: Epileptic seizures, Healthcare Applications, EEG Biomarkers, Machine Learning, Compound Biomarkers

1. INTRODUCTION

One of the most prevalent neurological disorders is epilepsy (Kanner et al., 2024). The neurobiological, cognitive, psychological, and social repercussions of seizure recurrences, as well as a lasting propensity to produce seizures that is not triggered by any acute central nervous system damage, are the hallmarks of this chronic brain disorder (Beghi, 2020). Seizures are not the only clinical signs; cognitive impairments and mental illnesses are frequent amongst them(Kanner et al., 2024). Worldwide, epilepsy affects people of all ages and genders (Beghi, 2020). Over 3 billion individuals globally suffered from a neurological disorder, including epilepsy, in 2021 (World Health Organization, 2024). There are 65 million epileptics around the globe (Milligan, 2021). An estimated $119.27 billion (USD) was spent on epilepsy worldwide in 2019 (Sharma et al., 2025). Epileptic seizures can occur repeatedly in people with the condition for no recognisable reason (R. Shankar et al., 2024).

Clinically, epilepsy can be diagnosed using different techniques such as Electroencephalogram (EEG), Magnetic Resonance Imaging (MRI), Computed Tomography (CT) Scan, and Magnetoencephalography (MEG), which show good results in diagnosing epilepsy (Adamczyk et al., 2021). However, the diagnose methods depend on EEG is the promising, EEG has uncovered the dynamic functioning of all brain areas throughout time (Al-Juboori, Mkwawa, Sun, & Ifeachor, 2017). EEG used to monitor the electricity of the brain cells that capture brain activities (A.H.H. Al-Nuaimi, Jammeh, Sun, & Ifeachor, 2018; Bogéa Ribeiro & da Silva Filho, 2023). Epilepsy-related brain alterations are reflected in EEG (Tian & Zhang, 2025).

Alterations in complicated brain networks have been scientifically monitored. Its low cost, reproducibility, non-invasiveness, and simply make it crucial for clinical evaluations of brain function (Ali H Husseen Al-Nuaimi, Al-Juboori, Jammeh, Sun, & Ifeachor, 2019). To identify pathophysiological brain networks and improve treatment

outcomes, EEG was integrated with other diagnosis techniques (Saridas & Demir, 2025)(A H Al-Nuaimi, Jammeh, Sun, & Ifeachor, 2017). It can be used to diagnose epilepsy with all ages (Islam, Basak, Islam, & Roy, 2023).

Artificial intelligence techniques such as Machine learning (ML) and deep learning (DL) provide a significant result in healthcare applications (Al-nuaimi, Nsaif, & Al-Juboori, 2025) (A.H. Al-Nuaimi, Jammeh, Sun, & Ifeachor, 2016; Armand, Nfor, Kim, & Kim, 2024). ML and DL techniques are commonly used to detect brain disorders such as Alzheimer's disease (Al-Kabi, Al-Tuwaijari, & Al-Nuaimi, 2023) (A. Singh & Kumar, 2024) (A.H. Al-Nuaimi, Jammeh, Sun, & Ifeachor, 2017), autism (Kumar & Jaiswal, 2025), and epilepsy (Han, Liu, & Friedman, 2024).

One-dimensional squeeze-and-excitation, or 1D SE, CNN (convolutional neural networks), BiLSTM (bidirectional long short-term memory), and an attention module were all combined to create the new detection model, which is called STFFDA (space-time feature fusion with dual attention). To classify the epileptic episodes, the 22 patients in the CHB-MIT EEG dataset were utilised to classify the epileptic seizures. The created model performed 92.42% for both recall and accuracy, and 92.47% for precision (Huang et al., 2025).

The RCMDE (Refine Composite Multiscale Dispersion Entropy) was examined to assess the complexity of seizures based on EEG research. To identify epilepsy, the ResCon-LSTM (Residual Convolutional Long Short-Term Memory) neural network was developed. The accuracy of the CHB-MIT dataset, which included 24 paediatric individuals with epilepsy, was 98.52% (Song, Fan, & Mao, 2024).

An EEG-based detection model, 1D-CNN (one-dimensional convolutional neural networks), optimised by MFO (moth-flame optimisation), was presented to assess the potential of using EEG to detect epileptic seizures. The model was assessed using the Bonn EEG dataset with five patients, achieving a maximum accuracy of 99.96 performance (Wang et al., 2023).

Epileptic seizure recognition by ML and DL was the main emphasis of the research. The dataset used for model development is the UCI-Epileptic Seizure Dataset. DL algorithms like ANN (Artificial Neural Network) and LSTM (long short-term memory) and ML techniques like LR (Logistic Regression), SVM (Support Vector Machine), and KNN (K-nearest Neighbour) were explored. The findings demonstrated that DL techniques performed better than ML techniques, with LR, SVM, and KNN demonstrating respective performances of 63.9%, 97.23%, and 91.96%. In contrast, DL's ANN and LSTM obtained 97% and 97.1%, respectively (Kunekar, Gupta, & Gaur, 2024).

A study was performed to examine the robustness of a collection of prospective biomarkers of seizure susceptibility. A total of 814 EEG recordings from 648 people. 129 for epilepsy, 281 for normal, and 152 for various diseases were acquired from eight National Health Service locations throughout the United Kingdom and included in the database were clinically non-contributory. Within each recording, eight computational markers were calculated: n is two for spectral, n is four for network-based, and n is two for model-based. Ensemble-based classifiers were created using a two-tier cross-validation approach. These weighted undirected networks were utilised to create four graph theoretical markers, and the low-alpha band phase-locking value between electrode pairs was calculated. These parameters comprised the usual path length, mean degree, degree variance, and average weighted clustering coefficient. The results revealed that the cohort with clinically non-contributory normal EEGs had a balanced accuracy of 68%, 61% for sensitivity, and 75% for specificity (Kunekar, Gupta, et al., 2024).

Categorising the ictal and inter-ictal phases of raw scalp EEG data, three deep-learning models; LSTM (long-short-term memory), RNN (Recurrent Neural Network), CNN (convolutional neural network) and LSTM (CNN-LSTM) were tested. Five epileptic and five healthy individuals' 40-minute ictal and non-ictal intracranial EEG data are included in the Bonn data set. The impact of various scalp EEG channel configurations on the identification of epileptic seizures was examined to manage the decrease in mobile devices that use behind-the-ear (BTE) electrodes. The sensitivity of the CNN-LSTM model was 73%. A promising sensitivity of 68% was obtained by using BTE channels as input to the suggested epileptic recognising seizures method (El-Dajani, Wilhelm, Baumann, Surges, & Meyer, 2025).

This paper is arranged as: Section two provides an explanation of the materials and methods used in the article. Section three displays the results, while Section four presents the discussion. The conclusion is in section five.

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

2. MATERIALS AND METHODS

2.1. Dataset

Five groups of EEG datasets (A, B, C, D, and E) were analysed (Andrzejak et al., 2001). Each group had one hundred fragments of a single channel with a sampling frequency of 173.61 Hz (Hertz), 23.59 seconds' duration for 4097 data points from the beginning of recording of the 4396 samples were selected for the analysis. After visually checking the continuous multichannel EEG recordings for artefacts, such as those caused by eye movements or muscle activity, these portions were chosen and removed.

The electrode locations for groups A and B were placed based on the 10-20 system as shown in Figure 1 which belongs to the five HC (Healthy Cognitive) groups, group A to eyes open and group B to eyes closed. While C, D, and E groups originated from pre-surgical diagnostics of the EEG signals. Five patients were chosen, and all of them obtained total SC (Seizure Control) following the removal of one of the hippocampus formations. As a result, the epileptogenic zone was accurately identified as shown in Figure 2. Fragments of groups C and D had only activity assessed during seizure-free times that were recorded from the hippocampal formation of the opposite hemisphere of the brain and from within the epileptogenic zone, respectively. While group E only contained seizure activity. The fragments were picked from all recording locations that showed ictal activity. The EEG dataset is available on the Bonn EEG time series download page (Universitat Pompeu Fabra Barcelona (UPF), n.d.).

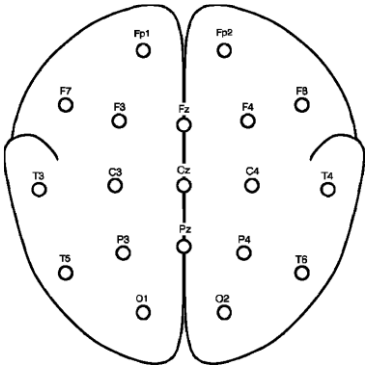

Figure 1: Electrodes positions in accordance with the internationally 10-20 system.

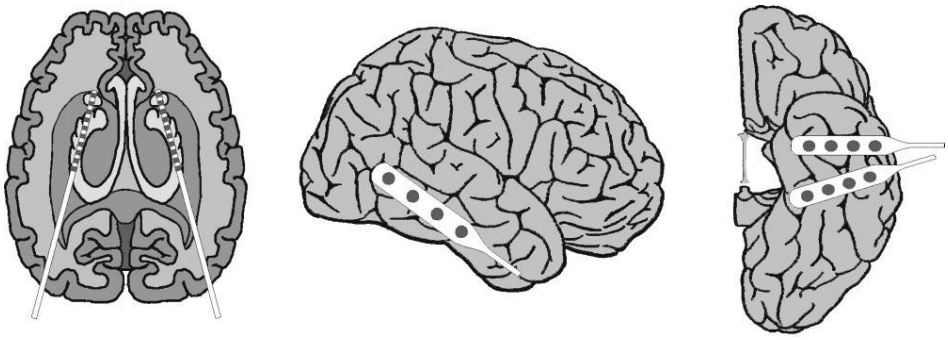

Figure 2: Configuration of intracranial electrodes used to assess individuals with epilepsy before surgery. The hippocampus formations were symmetrically implanted with depth electrodes (top)

2.2. Pipeline procedures for detecting epileptic seizures

2.2.1. Pre-processing

Chebyshev-II band-pass filter was used to filter the EEG signal between 0 and 45 Hz. To maintain valuable brainwave data like EEG where baseline drift and high-frequency noise must be reduced without changing the signal's morphology, Chebyshev Type II filters are especially helpful because of their flat passband and steep roll-off (Sörnmo & Laguna, 2005). Filtering the EEG signal to minimise noise and enhance data quality (de Cheveigné & Nelken, 2019).

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

2.2.2. Normalise the dataset

An attribute's range of values in a classification process can be very small or very large. The result of the classification process may be unfairly dominated by the attribute with a wide range of values just because of its higher values. Consequently, prior to classification, these variables need to be normalised (Sinsomboonthong, 2022). The EEG dataset was normalised using the following equation (Henderi, Wahyuningsih, & Rahwanto, 2021).

$$f(x_i) = \frac{x_i - \bar{x}}{\sigma} \qquad (1)$$

Where $f(x_i)$ is the normalised value of the data point x_i , x is time series signal likes EEG, $\bar{x}$ is the mean of x, σ is the standard deviation of x, i refers to the sequence of any data point in x, and N is the length of the signal x.

The EEG dataset was normalised to guarantee a consistency within the data samples (Benmabrouk et al., 2025).

2.2.3. Randomise the dataset:

Randomising data prior to model development could eliminate order bias and guarantee that patterns acquired by the model generalise effectively instead of overfitting to certain patterns (Kahan, Rehal, & Cro, 2015).

2.2.4. Partitioning the dataset

The EEG dataset was split into two subgroups: training with 60% and validating with 40% splitting rations, respectively.

2.2.5. Features developed

Eleven features were extracted from the EEG signal as a features vector.

The extracted features are

- Detrended Fluctuation Analysis (DFA) (Arsac & Deschodt-Arsac, 2018).

DFA is used to estimate the self-similarity and scaling property in fractal signals. It quantifies the fractal-scaling index of a physiological time series.

Physiological time-series and fractal scaling index were analysed using DFA. The scaling characteristics and self-similarity of fractal signals were calculated using DFA. The computation of DFA as follows

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2} \qquad (2)$$

$$y(k) = \sum_{i=1}^{k} x(i) - \bar{x} \qquad (3)$$

where $\bar{x}$ is the mean value of signal x.

A linear association on a log-log plot implies the presence of power law (fractal) scaling, and in such cases, the fluctuations can be attributed to a scaling exponent, the slope of the line relating log F(n) to log n. This calculation is carried out over all time scales (box sizes) to identify the interaction of F(n), the average fluctuation, and the box size n. Generally, F(n) will increase with box size.

- Skewness (Sk) and Kurtosis (Ku) (Karagiorgis, Ballis, & Drakos, 2023),

Skewness measures the asymmetry of a signal's distribution around its mean. Where:

$$x(i) = \frac{1}{N} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{\sigma} \right)^3 \qquad (4)$$

- x_i it is any data point with sequence i
- $\bar{x}$ is the mean of the signal

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

- σ is the standard deviation of signal x
- N is the length of the signal x

A measure of how heavy-tailed or light-tailed (outliers) the data are in comparison to a normal distribution is called kurtosis, as shown in Eq. (5)

$$x(i) = \frac{1}{N}\sum_{i=1}^{n}\left(\frac{x_i-\bar{x}}{\sigma}\right)^4 \qquad (5)$$

- Features from envelope (S. Ghosh, Dallmer-Zerbe, Buckova, & Hlinka, 2024).

The non-linearity of the EEG signal was measured using the Envelope Entropy (EnEp) to analyse the variability and complexity of the signal.

The envelope feature is calculated using the envelope entropy as shown

$$\text{EnEp} = -\sum_{i=1}^{N} p(i)\log(pi) \qquad (6)$$

where pi is the normalise probability distribution that computed as,

$$p(i) = \frac{A_i}{\sum_{i=1}^{n} A_i} \qquad (7)$$

Ai is the amplitude envelope value at time i that computed as,

$$A(i) = |z(i)| = \sqrt{x(i)^2 + H\{x(i)\}^2} \qquad (8)$$

where |z(i)| is the analytic signal which computed using Hilbert transform (H) of x

- Spectral Edge Frequency (SEF-95) (Poza, Hornero, Abásolo, Fernández, & García, 2007)

SEF95 measures the upper limit of the spectral content of the PSD (Power Spectral Density) of the signal and has been calculated to be the frequency that makes up 95% of the power. It calculated as

$$X = \sum_{i=1}^{95} PSD(x_i) \qquad (9)$$

- Instantaneous Frequency (IF) (Carcione, Gei, Picotti, & Botelho, 2021)

The values of mean (MIF), standard deviation (SIF), and variance (VIF) of IF were computed as features of the EEG signal. It is expressed by the rate of the phase change of a signal at any time. It is computed as

$$f(i) = \frac{1}{2\pi}.\frac{d\emptyset(i)}{di} \qquad (10)$$

Where dϕ(i)/di is the phase's derivative in relation to time i, and ϕ(i) is instantaneous phase which is calculated as

$$\emptyset(i) = \arg(z)\, i)) = tan^{-1}\left(\frac{H\{x(i)\}}{x(i)}\right) \qquad (11)$$

H{x(i)} is the Hilbert transform of x(i).

- Peak-to-Peak (P2P) amplitude (R. Ghosh et al., 2023)

P2P is the phase derivative of the signal in relation to its time. The computation of the P2P as

$$\text{P2P}=\max(x)-\min(x) \qquad (12)$$

- Autocorrelation Features (ACF) (Soriano & Zunino, 2021)

The relationship value between the signal's time and time delay is known as the ACF.

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

ACF at lag k is computed as

$$c_k = \frac{1}{N}\sum_{i=1}^{N-k}(x_i - \bar{x})(x_{i+k} - \bar{x}) \qquad (13)$$

The ACF is a relationship between x_i and x_{i+k}. The values of lag1 and lag2 were used as features when k=1, and 2.

The extracted eleven features were used to construct the features vector are:

DFA, Sk, Ku, EnEp, SEF-95, MIF, SIF, VIF, P2P, lag1, and lag2

2.2.6. Model development

ML models were utilised to develop an artificial intelligence (AI) detection system. The ML algorithms i.e., Logistic Regression (LR), Naive Bayes (NB), Neural Network (NN) that show a significant role in biomedical healthcare applications such as epilepsy detection have been investigated.

2.2.6. Model evaluation

The developed ML models were evaluated using the validation datasets; the remaining 40% of the EEG dataset. Sensitivity (Sen), Specificity (Spec), and Accuracy (Acc) were calculated for each of the three ML models as performance evaluation metrics.

3. RESULTS

Tables 1-6 describe the performance of the LR, NB, and NN detection models. 18 ML detection models were developed to detect the SC subjects.

Table 1 displays how well the LR, NB, and NN models discriminate between group C for with seizure-free periods and group A for HC with eyes open.

Table 1: The ML performance models between groups A for HC with eyes open and C for SC with seizure-free periods.

ML algorithm	Sen %	Spec %	Acc %
LR	96.67	85.29	90.00
NB	95.00	91.94	93.33
NN	96.67	98.31	97.50

Table 2 displays how well the LR, NB, and NN models discriminate between group C for with seizure-free periods and group B for HC with eyes closed.

Table 2: The ML performance models between groups B for HC with eyes closed and C for SC with seizure-free periods.

ML algorithm	Sen %	Spec %	Acc %
LR	98.33	93.65	95.83
NB	96.67	90.63	93.33
NN	96.67	90.63	93.33

Both tables 1 and 2 show high performance measures in detecting SC subjects of group C for SC with seizure-free periods and subjects of groups A and B for HC with eyes open and eyes closed to all the three investigated ML models.

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 3 displays how well the LR, NB, and NN models discriminate between group D for SC with epileptogenic zone and group A for HC with eyes open.

Table 3: The ML performance models between groups A for HC with eyes open and D for SC with epileptogenic zone

ML algorithm	Sen %	Spec %	Acc %
LR	98.33	93.65	95.83
NB	95.00	96.61	95.83
NN	98.33	92.19	95.00

Table 4 displays how well the LR, NB, and NN models discriminate between group D for SC with epileptogenic zone and group B for HC with eyes closed.

Table 4: The ML performance models between groups B for HC with eyes closed and D for SC with epileptogenic zone

ML algorithm	Sen %	Spec %	Acc %
LR	98.33	90.77	94.17
NB	98.33	90.77	94.17
NN	98.33	92.19	94.92

Both tables 3 and 4 show high performance measures in detecting SC subjects of group D for SC with epileptogenic zone and subjects of groups A and B for HC with eyes open and eyes closed to all the three investigated ML models.

Table 5 displays how well the LR, NB, and NN models discriminate between group E for SC with seizure activity and group A for HC with eyes open.

Table 5: The ML performance models between groups A for HC with eyes open and E for SC with seizure activity

ML algorithm	Sen %	Spec %	Acc %
LR	91.67	98.21	95.00
NB	98.33	98.33	98.33
NN	98.33	98.33	98.33

Table 6 displays how well the LR, NB, and NN models discriminate between group E for SC with seizure activity and group B for HC with eyes closed.

Table 6: The ML performance models between groups B for HC with eyes closed and E for SC with seizure activity

ML algorithm	Sen %	Spec %	Acc %
LR	96.67	98.31	97.50
NB	98.33	76.62	84.17
NN	98.33	84.29	90.00

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Both tables 3 and 4 show high performance measures in detecting SC subjects of group E for SC with seizure activity and subjects of groups A and B for HC with eyes open and eyes closed to all the three investigated ML models.

4. DISCUSSION

All ages and genders are affected by epilepsy (Beghi, 2020), and the exact causes and contributing factors are not well understood. In most cases, the cause of epilepsy was undetermined (Chahal et al., 2021), The precise aetiology of epilepsy is unclear in around 50% of instances (Heather Jones, 2023). Therefore, there is a need for simply, low cost, and invasiveness biomarkers (A.H. Al-Nuaimi, Jammeh, Sun, & Ifeachor, 2015). EEG is the most preferred tool that can be used to detect epileptic people.

In this study, different EEG biomarkers were integrated as a vector of features (compound biomarker). It is possible to improve detection performance by integrating several analytical methods (Ali H Al-Nuaimi et al., 2021). Improving detection performance might help to identify pathophysiological brain networks and improve treatment outcomes (Saridas & Demir, 2025).

Five groups of EEG datasets were used to validate the hypothesis of integrating several analytical methods to produce a compound biomarker. It includes HC and SC groups. A is for HC with eyes open, group B is for HC with eyes closed, group C is for SC with seizure-free times, group D is for SC with epileptogenic zone, and group E is for SC with seizure activity.

Eleven features extracted from EEG dataset, including the DFA, Sk, Ku, EnEp, SEF-95, MIF, SIF, VIF, P2P, lag1, and lag2 were incorporated as a compound biomarker to detect SC.

The HC, and SC groups were evaluated using the three ML methods, LR, NB, and NN. Therefore, 18-ML detection models were constructed to detect the SC subjects, as shown in tables 1-6.

The results in Table 7 demonstrated the performance summary of the LR model to distinguish between the SC people of groups C (seizure-free periods), D (epileptogenic zone), and E (seizure activity) of epileptics and the subjects of HC groups (A with eyes open, and B with eyes closed). The average performance of LR was 96.67%, 93.31%, and 94.72% for Sen, Spec, and Acc, respectively.

Table 7: The performance of LR diagnosing models

Dataset groups description	**Sen %**	**Spec %**	**Acc %**
A and C	96.67	85.29	90.00
B and C	98.33	93.65	95.83
A and D	98.33	93.65	95.83
B and D	98.33	90.77	94.17
A and E	91.67	98.21	95.00
B and E	96.67	98.31	97.50
Average of performance	96.67	93.31	94.72

The findings in Table 7 are compatible with the outcomes in other studies which used LR to detect seizures with 94.86% for average Acc, 96.71% for average precision, and 93.48% for Sen (Li, Qiao, Duan, & Miao, 2024). The results of Khan et al. (Khan, Khan, & Farooq, 2022) concluded that the LR method is a preferred ML method for detecting SC subjects, with performances of 93.39%, 91.16%, and 92.43 for Sen, Spec, and Acc, respectively. Another study used LR to discriminate between Sc and HC subjects and produced a performance of 73.44%, 100%, and 86.72% for Sen, Spec, and Acc, respectively (Deepa, Anand, Pandey, Pandey, & Karki, 2022). Results of the study achieved by Aliyu et al. (Aliyu & Lim, 2023) stated detecting the epileptic subjects by analysing the EEG signals using LR with performance of Acc 92%.

Journal of Information Systems Engineering and Management
2025, 10(39s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The results in Table 8 demonstrated the performance summary of the NB model to distinguish between the SC people of groups C (seizure-free periods), D (epileptogenic zone), and E (seizure activity) of epileptics and the subjects of HC groups (A with eyes open, and B with eyes closed). The average performance of NB was 96.94%, 90.82%, and 93.19% for Sen, Spec, and Acc, respectively.

Table 8: The performance of NB diagnosing models

Dataset groups description	Sen %	Spec %	Acc %
A and C	95.00	91.94	93.33
B and C	96.67	90.63	93.33
A and D	95.00	96.61	95.83
B and D	98.33	90.77	94.17
A and E	98.33	98.33	98.33
B and E	98.33	76.62	84.17
Average of performance	96.94	90.82	93.19

The findings in (Sameer & Gupta, 2021) provided 98% for the area under curve measure in recognising between ictal and healthy class using NB detection model. Singh et al. (M. Singh et al., 2023) evaluated the NB classifier in seizure recognition, and they found that NB is a promising classifier for analysing EEG signals to recognise SC subjects, with performance of 93.7%, 68%, and 88% for Acc, Sen, and precision, respectively. A study evaluating NB using EEG signals to detect ictal concluded that NB was a good classifier to detect ictal subjects, with performance of 100% for all the Acc, Sen, and Spec measures (Hadiyoso, Wijayanto, & Humairani, 2021). Another study investigated the NB classifier in detecting epileptic seizures based on analysing EEG signals and found that NB was a convenient classifier in detecting epileptic seizures, with performance of 88.7%, 97.9%, and 96% for Sen, Spec, and Acc, respectively (Kunekar, Kumawat, et al., 2024). These findings as shown in Table 8 are compatible with the results of this study that indicated that NB is a promising classifier in detecting the SC subjects which produces a high performance.

Table 9 shows the performance of the NN model to discriminating between the SC people of groups C (seizure-free periods), D (epileptogenic zone), and E (seizure activity) of epileptics and the subjects of HC groups (A with eyes open, and B with eyes closed). It summarises the average performance of the LR model with 97.78%, 92.66%, and 94.85% for Sen, Spec, and Acc, respectively.

Table 9: The performance of NN diagnosing models

Dataset groups description	Sen %	Spec %	Acc %
A and C	96.67	98.31	97.50
B and C	96.67	90.63	93.33
A and D	98.33	92.19	95.00
B and D	98.33	92.19	94.92
A and E	98.33	98.33	98.33
B and E	98.33	84.29	90.00
Average of performance	97.78	92.66	94.85

The results in Table 9 are compatible with the results in other studies (Guerrero, Parada, & Espitia, 2021) that indicated that NN is a good method for detecting epilepsy patients with an accuracy of 86.1%. The results presented by Shankar et al. (R. S. Shankar, Raminaidu, Raju, & Rajanikanth, 2021) indicated that ANN can be used to detect

the epileptic seizure with high performance of 97.55%, 91.48%, and 94.24% for Acc, Sen, and precision, respectively. Demirci et al. explored the ANN model to analyse EEG signals to recognise epileptic seizures. Their results showed the ANN performed a high recognition performance of 100% for Acc in seizure detection (Demirci, Demirci, & Engin, 2023). A study investigated the AAN for detecting seizure using EEG signal showed that ANN provided 97.60%, for the Acc.

The results in Table 9 are compatible with the results of other studies (Guerrero et al., 2021) that indicated that NN is a good method for detecting epilepsy patients with an accuracy of 86.1%. The results presented by Shankar et al. (R. S. Shankar et al., 2021) indicated that ANN can be used to detect epileptic seizures, with high performance of 97.55%, 91.48%, and 94.24% for Acc, Sen, and precision, respectively. Demirci et al. explored the ANN model to analyse EEG signals to recognise epileptic seizures. Their results showed the ANN performed a high recognition performance of 100% for Acc in seizure detection (Demirci et al., 2023). A study investigating the AAN for detecting seizures using EEG signals showed that ANN provided 97.60% for the Acc (Ech-Choudany, Scida, Assarar, Landré, & Bellach, 2020) .

The findings in this study indicated that integrating multiple EEG biomarkers as a compound biomarker could provide a high performance that may accelerate the diagnosis speeds. This acceleration could present more significance to clinical decision-making (Tait et al., 2024).

5. CONCLUSIONS

The findings of this study indicated that EEG signals are a promising tool for discovering the brain changes that are caused by epilepsy. Analysing EEG signals providing significant features might assist in developing a compound biomarker that could be used to identify people suffering from epileptic seizures. Integrating several analytical methods might improve detection performance. Furthermore, ML algorithms such as LR, NB, and NN classifiers showed a high efficiency of detection with a short time of the models' development.

Improving detection performance might help to identify pathophysiological brain networks and improve treatment outcomes. The future work will focus on evaluating the developed ML detection model using real-time EEG signals.

Supplementary Materials: The EEG dataset used in this study is available at https://www.upf.edu/.

Extra information about the dataset is available at
https://www.upf.edu/documents/229517819/232450661/Andrzejak-PhysicalReviewE2001.pdf/0e9a54b8-8993-b400-743e-4d64fa29fb63

Funding: "This research received no funding".

Data Availability Statement: The EEG dataset used in this study is available at https://www.upf.edu/.

Acknowledgments: The dataset used in this study was by the Universitat Pompeu Fabra Barcelona (UPF).

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

REFERENCES

[1]. Adamczyk, B., Węgrzyn, K., Wilczyński, T., Maciarz, J., Morawiec, N., & Adamczyk-Sowa, M. (2021). The most common lesions detected by neuroimaging as causes of epilepsy. *Medicina*, *57*(3), 294.

[2]. Aliyu, I., & Lim, C. G. (2023). Selection of optimal wavelet features for epileptic EEG signal classification with LSTM. *Neural Computing and Applications*, 1–21.

[3]. Al-Juboori, S., Mkwawa, I.-H., Sun, L., & Ifeachor, E. (2017). Investigation of relationships between changes in EEG features and subjective quality of HDR images. In *2017 IEEE International Conference on Multimedia and Expo (ICME)* (pp. 91–96). IEEE.

[4]. Al-Kabi, H. D. S., Al-Tuwaijari, J. M., & Al-Nuaimi, A. H. H. (2023). ML-based methods for detection of AD and MCI using blood biomarkers. In *AIP Conference Proceedings* (Vol. 2834). AIP Publishing.

[5]. Al-Nuaimi, A H, Jammeh, E., Sun, L., & Ifeachor, E. (2017). Changes in the Electroencephalogram as a Biomarker of Alzheimer's Disease. In *Proceedings of the Biosense Dementia 2017-international workshop on biosensors for dementia from 13–14 June 2017*.

[6]. Al-nuaimi, A., Nsaif, M. K., & Al-Juboori, S. (2025). Developing an Artificial Intelligence Framework for Identifying Fusion Blood-Based Biomarkers in Alzheimer's Disease. *Journal of Information Systems Engineering and Management*, *10*(36s), 443. https://doi.org/https://doi.org/10.52783/jisem.v10i36s.6513

[7]. Al-Nuaimi, A.H., Jammeh, E., Sun, L., & Ifeachor, E. (2015). Tsallis entropy as a biomarker for detection of Alzheimer's disease. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (Vol. 2015-Novem). https://doi.org/10.1109/EMBC.2015.7319312

[8]. Al-Nuaimi, A.H., Jammeh, E., Sun, L., & Ifeachor, E. (2016). Changes in the EEG amplitude as a biomarker for early detection of Alzheimer's disease. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (Vol. 2016-Octob). https://doi.org/10.1109/EMBC.2016.7590869

[9]. Al-Nuaimi, A.H., Jammeh, E., Sun, L., & Ifeachor, E. (2017). Higuchi fractal dimension of the electroencephalogram as a biomarker for early detection of Alzheimer's disease. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. https://doi.org/10.1109/EMBC.2017.8037320

[10]. Al-Nuaimi, A.H.H., Jammeh, E., Sun, L., & Ifeachor, E. (2018). Complexity Measures for Quantifying Changes in Electroencephalogram in Alzheimer's Disease. *Complexity*, *2018*. https://doi.org/10.1155/2018/8915079

[11]. Al-Nuaimi, Ali H, Blūma, M., Al-Juboori, S. S., Eke, C. S., Jammeh, E., Sun, L., & Ifeachor, E. (2021). Robust EEG based biomarkers to detect Alzheimer's disease. *Brain Sciences*, *11*(8), 1026.

[12]. Al-Nuaimi, Ali H Husseen, Al-Juboori, S., Jammeh, E., Sun, L., & Ifeachor, E. (2019). Electroencephalogram based biomarkers for detection of Alzheimer's disease. In *Neuroimaging-Neurobiology, Multimodal and Network Applications*. IntechOpen.

[13]. Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., & Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, *64*(6), 061907.

[14]. Armand, T. P. T., Nfor, K. A., Kim, J.-I., & Kim, H.-C. (2024). Applications of artificial intelligence, machine learning, and deep learning in nutrition: a systematic review. *Nutrients*, *16*(7), 1073.

[15]. Arsac, L. M., & Deschodt-Arsac, V. (2018). Detrended fluctuation analysis in a simple spreadsheet as a tool for teaching fractal physiology. *Advances in Physiology Education*, *42*(3), 493–499.

[16]. Beghi, E. (2020). The epidemiology of epilepsy. *Neuroepidemiology*, *54*(2), 185–191.

[17]. Benmabrouk, Y., Djaffal, S., Gasmi, M., Djeddi, C., Diaz, M., & Bendjenna, H. (2025). Enhancing breast cancer histopathological image classification: The impact of stain normalization on multilevel feature extraction. *Biomedical Signal Processing and Control*, *106*, 107700. https://doi.org/https://doi.org/10.1016/j.bspc.2025.107700

[18]. Bogéa Ribeiro, L., & da Silva Filho, M. (2023). Systematic review on EEG analysis to diagnose and treat autism by evaluating functional connectivity and spectral power. *Neuropsychiatric Disease and Treatment*, 415–424.

[19]. Carcione, J. M., Gei, D., Picotti, S., & Botelho, M. A. B. (2021). On the instantaneous frequency and quality factor. *Geophysical Journal International*, *227*(2), 735–745.

[20]. Chahal, C. A. A., Tester, D. J., Fayyaz, A. U., Jaliparthy, K., Khan, N. A., Lu, D., Khan, M., Sahoo, A., Rajendran, A., & Knight, J. A. (2021). Confirmation of cause of death via comprehensive autopsy and whole exome molecular sequencing in people with epilepsy and sudden unexpected death. *Journal of the American Heart Association*, *10*(23), e021170.

[21]. de Cheveigné, A., & Nelken, I. (2019). Filters: When, Why, and How (Not) to Use Them. *Neuron*, *102*(2), 280–293. https://doi.org/https://doi.org/10.1016/j.neuron.2019.02.039

[22]. Deepa, R., Anand, R., Pandey, D., Pandey, B. K., & Karki, B. (2022). Comprehensive performance analysis of classifiers in diagnosis of epilepsy. *Mathematical Problems in Engineering*, *2022*(1), 1559312.

[23]. Demirci, B. A., Demirci, O., & Engin, M. (2023). Comparative analysis of ANN performance of four feature extraction methods used in the detection of epileptic seizures. *Computers in Biology and Medicine*, *166*, 107491.

[24]. Ech-Choudany, Y., Scida, D., Assarar, M., Landré, J., & Bellach, B. (2020). Dissimilarity-based time—frequency distributions as features for epileptic EEG signal classification To cite this version: HAL Id: hal-02973615. HAL Open Sci 64: 0–24.

[25]. El-Dajani, N., Wilhelm, T. F. L., Baumann, J., Surges, R., & Meyer, B. T. (2025). Patient-Independent Epileptic Seizure Detection with Reduced EEG Channels and Deep Recurrent Neural Networks. *Information*, *16*(1), 20.

[26]. Ghosh, R., Phadikar, S., Deb, N., Sinha, N., Das, P., & Ghaderpour, E. (2023). Automatic eyeblink and muscular artifact detection and removal from EEG signals using k-nearest neighbor classifier and long short-term memory networks. *IEEE Sensors Journal*, *23*(5), 5422–5436.

[27]. Ghosh, S., Dallmer-Zerbe, I., Buckova, B. R., & Hlinka, J. (2024). Amplitude entropy to capture chimera-like behavior in the altered brain dynamics during seizures. *BioRxiv*, 2024–2025.

[28]. Guerrero, M. C., Parada, J. S., & Espitia, H. E. (2021). EEG signal analysis using classification techniques: Logistic regression, artificial neural networks, support vector machines, and convolutional neural networks. *Heliyon*, *7*(6).

[29]. Hadiyoso, S., Wijayanto, I., & Humairani, A. (2021). Signal Dynamics Analysis for Epileptic Seizure Classification on EEG Signals. *Traitement Du Signal*, *38*(1), 73–78.

[30]. Han, K., Liu, C., & Friedman, D. (2024). Artificial intelligence/machine learning for epilepsy and seizure diagnosis. *Epilepsy & Behavior*, *155*, 109736.

[31]. Heather Jones. (2023, August 16). Is Epilepsy Genetic? Retrieved 13 April 2025, from https://www.verywellhealth.com/is-epilepsy-genetic-6826125

[32]. Henderi, H., Wahyuningsih, T., & Rahwanto, E. (2021). Comparison of Min-Max normalization and Z-Score Normalization in the K-nearest neighbor (kNN) Algorithm to Test the Accuracy of Types of Breast Cancer. *International Journal of Informatics and Information Systems*, *4*(1), 13–20.

[33]. Huang, Z., Yang, Y., Ma, Y., Dong, Q., Su, J., Shi, H., Zhang, S., & Hu, L. (2025). EEG detection and recognition model for epilepsy based on dual attention mechanism. *Scientific Reports*, *15*(1), 9404.

[34]. Islam, T., Basak, M., Islam, R., & Roy, A. D. (2023). Investigating population-specific epilepsy detection from noisy EEG signals using deep-learning models. *Heliyon*, *9*(12).

[35]. Kahan, B. C., Rehal, S., & Cro, S. (2015). Risk of selection bias in randomised trials. *Trials*, *16*, 1–7.

[36]. Kanner, A. M., Shankar, R., Margraf, N. G., Schmitz, B., Ben-Menachem, E., & Sander, J. W. (2024). Mood disorders in adults with epilepsy: a review of unrecognized facts and common misconceptions. *Annals of General Psychiatry*, *23*(1), 11.

[37]. Karagiorgis, A., Ballis, A., & Drakos, K. (2023). The Skewness-Kurtosis plane for cryptocurrencies' universe, Intl. *Journal of Finance and Economics, John Wiley, Https://Doi. Org/10.1002/Ijfe*, *2795*.

[38]. Khan, I. M., Khan, M. M., & Farooq, O. (2022). Epileptic seizure detection using EEG signals. In *2022 5th International Conference on Computing and Informatics (ICCI)* (pp. 111–117). IEEE.

[39]. Kumar, A., & Jaiswal, U. C. (2025). Predicting Autism Spectrum Disorder in Adults Through Facial Image Analysis: A Multi-CNN with BiLSTM Model. *SN Computer Science*, *6*(3), 254.

[40]. Kunekar, P., Gupta, M. K., & Gaur, P. (2024). Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques. *Journal of Engineering and Applied Science*, *71*(1), 21.

[41]. Kunekar, P., Kumawat, C., Lande, V., Lokhande, S., Mandhana, R., & Kshirsagar, M. (2024). Comparison of different machine learning algorithms to classify epilepsy seizure from eeg signals. *Engineering Proceedings*, *59*(1), 166.

[42]. Li, X., Qiao, Y., Duan, L., & Miao, J. (2024). Epilepsy EEG signals classification based on sparse principal component logistic regression model. *Computer Methods in Biomechanics and Biomedical Engineering*, 1–9.

[43]. Milligan, T. A. (2021). Epilepsy: a clinical overview. *The American Journal of Medicine*, *134*(7), 840–847.

[44]. Poza, J., Hornero, R., Abásolo, D., Fernández, A., & García, M. (2007). Extraction of spectral based measures from MEG background oscillations in Alzheimer's disease. *Medical Engineering & Physics*, *29*(10), 1073–1083.

[45]. Sameer, M., & Gupta, B. (2021). ROC analysis of EEG subbands for epileptic seizure detection using naïve bayes classifier. *Journal of Mobile Multimedia*, 299–310.

[46]. Saridas, F., & Demir, A. B. (2025). The Role of Video EEG Monitoring in Epilepsy Diagnosis and Treatment Processes.

[47]. Shankar, R., Marston, X. L., Danielson, V., Do Rego, B., Lasagne, R., Williams, O., & Groves, L. (2024). Real-world evidence of epidemiology, patient characteristics, and mortality in people with drug-resistant epilepsy in the United Kingdom, 2011–2021. *Journal of Neurology*, *271*(5), 2473–2483.

Research Article

[48]. Shankar, R. S., Raminaidu, C. H., Raju, V. V. S., & Rajanikanth, J. (2021). Detection of Epilepsy based on EEG Signals using PCA with ANN Model. In *Journal of Physics: Conference Series* (Vol. 2070, p. 012145). IOP Publishing.

[49]. Sharma, R., Schinasi, L. H., Lee, B. K., Weuve, J., Weisskopf, M. G., Sheffield, P. E., & Clougherty, J. E. (2025). Air Pollution and Temperature in Seizures and Epilepsy: A Scoping Review of Epidemiological Studies. *Current Environmental Health Reports*, *12*(1), 1–15.

[50]. Singh, A., & Kumar, R. (2024). Brain MRI image analysis for Alzheimer's disease (AD) prediction using deep learning approaches. *SN Computer Science*, *5*(1), 160.

[51]. Singh, M., Jagyasi, G., Garg, M., Jain, A., Gupta, N., Kumar, K., & Kumar, A. (2023). A Machine Learning Framework for Robust Epileptic Seizure Detection from EEG Sign. In *2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)* (pp. 1–4). IEEE.

[52]. Sinsomboonthong, S. (2022). Performance Comparison of New Adjusted Min-Max with Decimal Scaling and Statistical Column Normalization Methods for Artificial Neural Network Classification. *International Journal of Mathematics and Mathematical Sciences*, *2022*(1), 3584406.

[53]. Song, Y., Fan, C., & Mao, X. (2024). Optimization of epilepsy detection method based on dynamic EEG channel screening. *Neural Networks*, *172*, 106119.

[54]. Soriano, M. C., & Zunino, L. (2021). Time-delay identification using multiscale ordinal quantifiers. *Entropy*, *23*(8), 969.

[55]. Sörnmo, L., & Laguna, P. (2005). *Bioelectrical signal processing in cardiac and neurological applications*. Academic press.

[56]. Tait, L., Staniaszek, L. E., Galizia, E., Martin-Lopez, D., Walker, M. C., Azeez, A. A. A., Meiklejohn, K., Allen, D., Price, C., & Georgiou, S. (2024). Estimating the likelihood of epilepsy from clinically noncontributory electroencephalograms using computational analysis: A retrospective, multisite case–control study. *Epilepsia*, *65*(8), 2459–2469.

[57]. Tian, C., & Zhang, F. (2025). EEG-based epilepsy detection with graph correlation analysis. *Frontiers in Medicine*, *12*, 1549491.

[58]. Universitat Pompeu Fabra Barcelona (UPF). (n.d.). The Bonn EEG time series download page. Retrieved 3 April 2025, from https://www.upf.edu/

[59]. Wang, B., Yang, X., Li, S., Wang, W., Ouyang, Y., Zhou, J., & Wang, C. (2023). Automatic epileptic seizure detection based on EEG using a moth-flame optimization of one-dimensional convolutional neural networks. *Frontiers in Neuroscience*, *17*, 1291608.

[60]. World Health Organization. (2024, April 14). World Federation of Neurology - Fostering quality neurology and brain health worldwide. Retrieved 10 April 2025, from https://wfneurology.org/activities/news-events/archived-news/2024-03-15-who?utm_source=chatgpt.com