Deep Neural Network Model for Automated Detection of Alzheimer's Disease using EEG Signals

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Abstract—Our brain is our body's control centre and is essential for proper functioning of the body. Alzheimer's disease is a chronic neurodegenerative disease that affects the cerebral cortex of the brain and causes memory loss and loss of cognitive thinking. EEG (Electroencephalography) is a method of recording neurological electrical activity with electrodes. It was chosen as it is a simple, painless procedure. This paper suggests an automated and accurate algorithm for the detection of Alzheimer's Disease using EEG signals with a combination of Signal processing and Deep Learning Methods. Concepts like Butterworth filters, DWT, statistical parameters, Data Augmentation and CNN were used in order to achieve a classification algorithm with high accuracy. A total highest system accuracy of 97.61% was achieved.

Keywords—electroencephalography, Alzheimer's disease, filters, discrete wavelet transform, statistical features, conditional generative adversarial network, convolutional neural network, long short-term memory

1 Introduction

In modern medicine, EEG is one of the most common diagnostic tests for brain disorders. EEG is defined as the recording of the brain's electrical activity. Voltage fluctuations in different regions of the brain are measured with the help of adhesive electrodes placed on the scalp at predetermined positions.

The use of EEG signals has proved advantageous, mainly since the method is non-invasive in nature. EEG also provides a high temporal resolution, typically in the order of milliseconds. Radiation risks posed by typical diagnostic methods like MRI's and CT-Scans and the invasive nature of clinical methods have popularized the use of EEG.

Alzheimer's disease (AD) is a chronic neurodegenerative disease. It is the most common type of dementia prevalent in older people. It affects one in fifteen people over the age of 65. The cause of AD is still unclear but it is known that it is caused due to extreme shrinkage in the Cerebral Cortex and Hippocampus regions of the brain. Early detection of AD is crucial in order to reduce or delay further progression of the disease.

Alzheimer's disease research with EEG can be understood in terms of the type of features used. Typically, the features, or Biomarkers, can broadly be classified into 3 types: Time Domain Feature, Frequency domain features and Time-Frequency

domain features. Other methods include using Classical Machine Learning or Neural Network models for classification of raw EEG signals. Since EEG is a non-stationary signal, it is more appropriate to use time-frequency based approaches like DWT (Discrete Wavelet Transform), for feature extraction. Once these features are obtained, the dataset can be used to train a classifier to classify the signal as an AD patient or normal. In the proposed work, a CNN algorithm was used.

The main motivation for this work is based of existing research conducted by Yasmeen et al [1]. The work proposes the use of EEG signals and feed forward neural networks for the diagnosis of Seizures. The paper proposes the use of features like DWT as time-frequency biomarkers in classification. It also suggests the use of classical ML algorithms to determine the most optimum channels of the EEG dataset with the help of statistical features like mean, variance, standard deviation, kurtosis and skewness. With the help of 2 datasets at different sampling frequencies, an ANN algorithm was trained, which achieved an average classification accuracy of 95%.

This work aims to build on any existing research in the field of EEG signal analysis and automated Disease detection algorithms using Neural Networks.

2 Review

An extensive literature survey indicates that automated diagnosis of brain disorders using EEG signals is being researched extensively globally.

Gao Wei Xu et al [2] suggest an algorithm for detection for epileptic seizures for both binary and 5-class problems. The paper suggests the use of a 1-D CNN-LSTM Model. Since CNN's cannot retain memory of previous time series patterns, this paper suggests the use of a hybrid CNN model. The model utilises an LSTM block, which is traditionally used in RNN algorithms, in order to serve as a memory unit. The method is established as more effective, providing a classification accuracy of 99.39% for the binary classifier and 82% for five classes.

A technical review performed by Bibina et al [3] on signal processing methods for Diagnosing Alzheimer's Disease using EEG gives a comparative study of different time, frequency and time-frequency biomarkers used in analysis. It highlights the benefits of using time-frequency features for classification. The paper also suggests that SVM and ANN algorithms are important for ECG classification tasks.

Applications and comparisons of classification algorithms for recognition of Alzheimer's Disease by Lehmann et al [4] suggests the use of absolute and relative spectral power biomarkers calculated from recording of rested eyes closed EEG signals taken from healthy, mild and moderate cases of AD. It also suggests the use of algorithms like forest classification, SVM and neural networks for classification achieving accuracies as high as 91% for Severe AD vs Normal classifications.

Mike Cohen [5] provides a definitive pre-processing pipeline and segmentation methods for EEG signals. His work also provides solutions to reject channel noise.

Lei Xu et al [6] suggested a method to sample tabular data and generate synthetic data samples of high fidelity. The proposed CTGAN algorithm is designed to train-by-sampling, which helps to overcome imbalanced columns of data. It uses mode-specific normalization to overcome non-gaussian and multimodal distributions. CTGAN was used as a data augmentation method.

A review performed by Cassani et al [7] is a comprehensive study of EEG data. It suggests that the ideal number of electrodes to record EEG data is 17–32 electrodes. It also highlights the use of pre-processing filters and notch filters to remove noise and power-grid interference in EEG signals.

3 Methodology

Block diagram of the proposed method for detection of AD has been shown in Figure 1. It includes data acquisition, preprocessing, feature extraction channel selection followed by data augmentation and classification. Each block of the diagram is explained in brief.

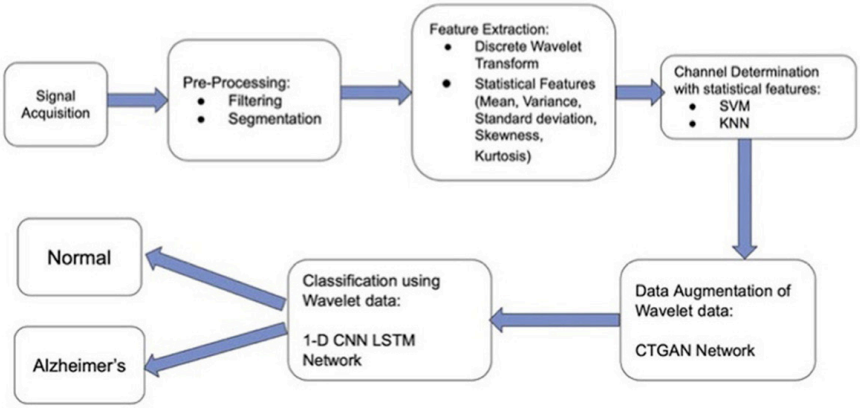

Fig. 1. Block diagram

The raw EEG signal acquired was initially given for pre-processing. Filtering performed on the signal included the use of a Butterworth Band-Pass filter in order to obtain the ideal EEG Signal range (0 Hz–60 Hz). Also, in order to remove power-line interference, a notch filter was used at 50 Hz.

After denoising, the signal was further segmented using a window size of 60 sec. From each sample of data, 6 segments from the middle were extracted and sent for feature extraction. Daubechies DWT is applied to the resultant dataset in order to obtain the different sub-bands of EEG such as gamma (>32 Hz), beta (16–31 Hz), alpha (8–15 Hz), theta (4–7 Hz) and delta (<4 Hz).

Statistical features are calculated for each sub-band obtained from DWT. Features like mean, variance, standard deviation, skewness and kurtosis are calculated for each channel. Classical ML algorithms, like SVM and KNN were trained channel-wise, in order to compare classification accuracies between AD and Normal. The higher the classification accuracy, the more optimal the channel for AD classification.

The initial 28 channels were shortlisted to 10 channels and these 10 channels were passed through a CTGAN data augmentation function. This step is performed in order to have more samples by generating synthetic data using Generative Adversarial Network Models. More data samples are needed for a more robust and accurate Classifier.

Once the final data augmented dataset is obtained, a 1-D Convolutional Neural Network with Long Short-Term Memory module is trained as a classifier to classify the signal as AD or Normal.

4 Implementation

In the proposed work, a dataset was obtained from the Department of Neuroscience, Ramaiah Memorial Hospital. The data was recorded using an EEG electrode cap following the standard 10–20 system of electrode placement. In this system, electrodes are placed at every 10% of total front-back distance and 20% of the total left-right distance of the scalp. A total of **28** channels are present in the dataset. The dataset was sampled at 128 Hz and was handled as Comma Separated (.csv) files. The simulation environment used in this paper is Python (version 3.7.11).

4.1 Pre-processing

Pre-processing is required for EEG signals in order to remove any discrepancies in the signal. Eye-blink artefacts, power-line noise and other noises can all be removed using signal processing techniques.

The signal in the range of **0–60 Hz** is the only part of the signal that contains the sub-band's in EEG signals, the rest is classified as noise. Hence, a bandpass filter from 0–60 Hz was designed to attenuate unwanted frequencies. The bandpass was constructed as a combination of 6th order high-pass and low-pass Butterworth filter. Furthermore, to remove power-line artefacts, an IIR notch filter is implemented at **50 Hz**. The signal which is passed through the combination of these filters has a higher signal-to-noise ratio.

This denoised signal is segmented into segments of **60 sec** each. With a sampling frequency of **128 Hz**, we can conclude that there are **7860** samples of data per segment. Out of the **18–22** segments obtained per sample, we consider only the middle six segments from each sample. This is done in order to remove any biases in the data based on subjects restlessness or eye-blinks. A final total of **155** segments of data were obtained.

4.2 Feature extraction

Discrete wavelet transform. Initially the Power Spectral Density biomarker was considered for analysis. However, PSD cannot represent the abrupt changes present in the EEG signal efficiently. Since EEG is a non-stationary signal, it is more advantageous to use a time-frequency domain-based biomarker. Wavelets are oscillations like waves, and have features like scaling and shifting. Since it works on a multi-scale basis it allows for decomposition of EEG signals.

The type of wavelet transform plays an important role as it is crucial in obtaining the correct frequency bands. Daubechies wavelets are a family of orthogonal wavelets

which have a smoothing feature. The sub-bands can be effectively extracted using a db4 wavelet transform algorithm. A total of five decomposition levels are obtained from the EEG signal, namely, detail coefficients D1 (64–128 Hz), D2 (32–64 Hz), D3 (16–32 Hz), D4 (8–16 Hz), D5 (4–8 Hz) and approximation coefficient A5 (0–4 Hz) are obtained. Figure 2 represents a plot of the sub-bands extracted from the dataset, using Discrete Wavelet Transform.

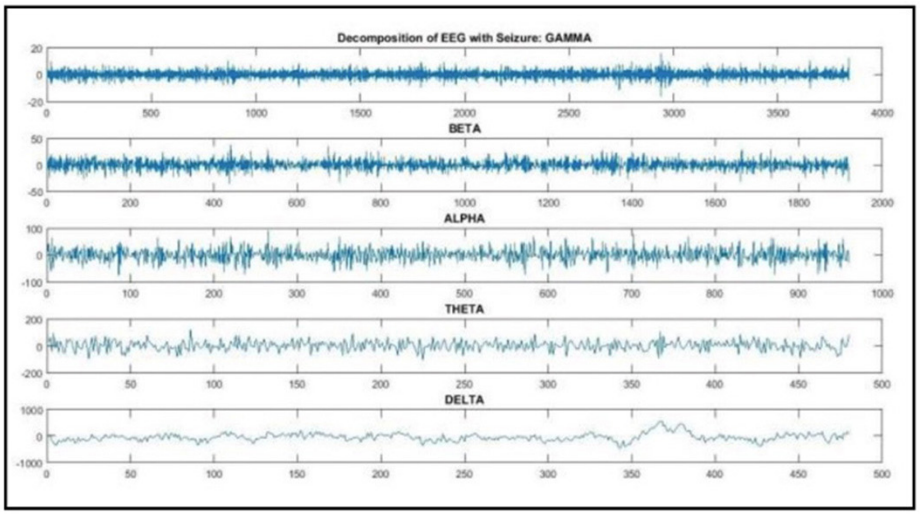

Fig. 2. Decomposition of EEG signal

The Table 1 shows the various decomposition levels and their corresponding sub-bands. Therefore D2, D3, D4, D5 and A5 were used for further statistical feature extraction.

Table 1. Wavelet transform and sub-bands

Sub-Bands	Frequency Bands	Decomposition Level
Noise	64–128 Hz	D1
Gamma	32–64 Hz	D2
Beta	16–32 Hz	D3
Alpha	8–16 Hz	D4
Theta	4–8 Hz	D5
Delta	0–4 Hz	A5

The DWT features extracted represent the distribution of the energy of the signal on a time-frequency scale. Since we are aware that not all the channels contain data that defines AD, we must reduce the channels in the data to only those which are useful. The main aim is to obtain the 10 best channels for AD classification.

Statistical features. In order to reduce the dimensionality of the problem, we calculate statistical parameters for these DWT features. As per previous literature, we have considered the statistical moments up to **4th** order, i.e., mean, variance, skewness and kurtosis. We have also considered standard deviation, for this work.

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- **Mean:** Mean is considered as first statistical moment, around zero. Mean calculate the value around which centrally clustering occurs.

$$\bar{x} = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{1}$$

- **Variance:** The second moment around the mean is variance which gives the spread or scale of distribution.

$$Var(x_1 \ldots x_N) = \frac{1}{N}\sum_{j=1}^{N} (x_j - \bar{x})^2 \tag{2}$$

- **Standard Deviation:** Standard deviation measures dispersion or width of the distribution. It can also be termed as the square root of variance.

$$\sigma(x_1 \ldots x_N) = \sqrt{Var(x_1 \ldots x_N)} \tag{3}$$

- **Skewness:** The third moment defines the skewness of distribution. It shows the asymmetry of distribution around its mean. A positive value signifies the tail of distribution extends towards more positive and negative values signifies tail towards more negative of x.

$$Skew(x_1 \ldots x_N) = \frac{1}{N}\sum_{j=1}^{N} \left[\frac{x_j - \bar{x}}{\sigma}\right]^3 \tag{4}$$

- **Kurtosis:** It is a non-dimensional quantity which measures the flatness or the peaked-ness of distribution. A positive kurtosis value is termed as leptokurtic, and negative kurtosis is termed as platykurtic.

$$Kurt(x_1 \ldots x_N) = \left\{\frac{1}{N}\sum_{j=1}^{N} \left[\frac{x_j - \bar{x}}{\sigma}\right]^4\right\} - 3 \tag{5}$$

The calculation was done sub-band wise for each channel of data. The final feature set can be defined as follows, for each sample of data: **25** Parameters/Per channel. When we consider the whole statistical feature set, we have **1050** Data Values per Channel.

4.3 Channel determination

The final feature set obtained cannot be analysed by mere manual observations. To get a better understanding of the channels, we use classical Machine Learning algorithms. In this work, we have used Support Vector Machine (**SVM**) and K Nearest Neighbours (**KNN**) algorithms.

SVM's are supervised learning models which are mainly used in classification problems. It is a linear classifier where the data point is considered as a p-dimensional vector. The algorithm develops a (p-1) – dimensional hyperplane. For this implementation, an SVM with '**rbf**' kernel function was chosen.

KNN algorithms are supervised and non-parametric methods used for classification. The data is used to train the model and the K value denotes the K nearest data points to the test point. The most frequent class value in the K points is the class assigned to the test data. The best results are observed with '**6**' Nearest Neighbours for KNN classifier.

A channel-wise comparison is done using these models, in order to ascertain the best **10** channels for further work. Table 2 represent the 10 best channels obtained and the corresponding accuracy scores for both SVM and KNN models.

Table 2. SVM and KNN accuracies

Channel Name	SVM Accuracy	KNN Accuracy
EMG (Highest Accuracy)	69.64%	76.00%
Fp2	69.69%	64.00%
Fp1	70.21%	62.05%
EKG	68.92%	63.18%
A2	68.72%	61.38%
PG1	68.36%	61.13%
C4	67.64%	63.03%
T4	66.82%	62.66%
F7	68.36%	60.56%
F3	66.92%	61.33%
MK (Example of bad channel)	64.36%	56.82%

4.4 Data augmentation

Upon determining the 10 best channels, the overall dataset size was drastically reduced. Since the work uses a CNN algorithm, a large dataset is beneficial for the network. In order to eliminate the data discrepancy, data augmentation was used. Literature suggests Generative Adversarial Networks (**GAN**) to be best suited for this application.

GAN Networks are deep-learning based generative models, consisting of a generator and discriminator sub-model. This work uses only the generator model, which uses an existing dataset to train the model and then creates synthetic clones.

CTGAN or conditional GAN architecture was chosen since it is a deep learning based synthetic data generator for single table data. CTGAN can produce clones with high fidelity with the use of features like mode-specific normalisation and performing training-by-sampling. It also overcomes problems like imbalanced columns of data. CTGAN network uses Adam optimization and was trained for 10 epochs.

The Figure 3 represents the architecture of CTGAN, in terms of its generator and critic model. In this work, the generator model was solely used.

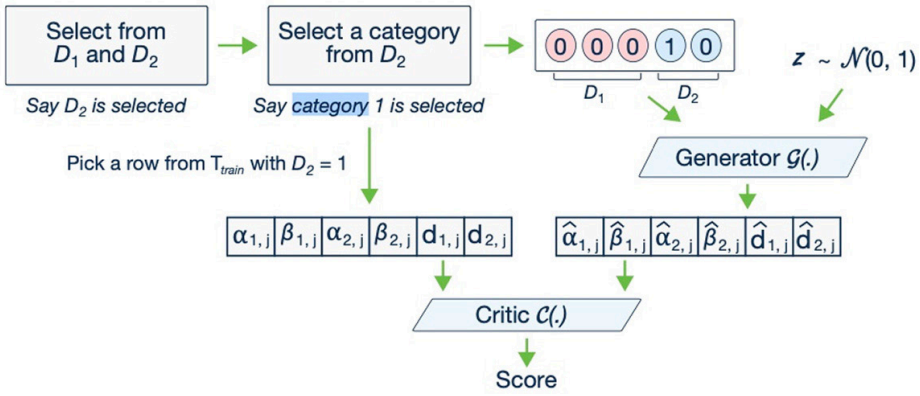

Fig. 3. CTGAN architecture

4.5 CNN algorithm (classifier)

CNN models are a relatively newer and more accurate method for creating classification models. This method makes use of Convolutional layers and the model is trained using data in Batches and Epochs. At each epoch, the model is more accurate and hence it can view patterns in data more easily. In recent research trends, CNN models are preferred over traditional RNN algorithms.

The proposed **1D CNN-LSTM** model is composed of an input layer, one convolutional layer, one pooling layer, one LSTM layer and a dense layer. The Figure 4 represents the detailed model architecture.

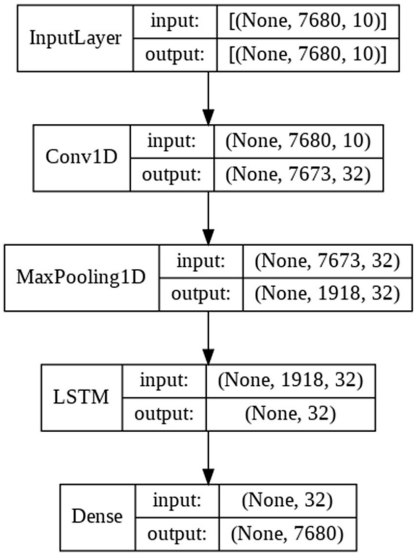

Fig. 4. 1-D CNN model with LSTM layer architecture

The input layer has a shape of **(X, 7680, 10)**, where X represents the number of segments. This layer can extract abstract features from the signal.

The input layer is then passed through to the 1-D convolutional layer. The input layer has a kernel size of 8 with 32 filters. A Rectified Linear Unit (**ReLu**) activation layer is used, which can introduce non-linearity to the model.

The feature maps generated in the input layer are sent to the Max-Pooling layer. In this layer, the size of the pooling window is 4 and the stride of the window is also 4. The max-pooling layer helps to reduce the dimensionality of the training and accelerates the training process.

After passing through the Max-Pooling layer, the feature maps are passed through to the LSTM layer. LSTM is an RNN based concept which is similar to a memory unit. The LSTM layer can preserve previous information and further improve the learning ability of the model from continuous EEG data. The layer used has a kernel size of **32** with a **Sigmoid** recurrent activation function.

Finally, the features are passed to the Dense layer. This layer is responsible for the final classification of the data. It utilizes a Rectified Linear Unit (ReLu) activation layer, similar to the input layer. The final feature which is output is the class of the testing data.

5 Results and conclusion

In this study, a single dataset, sampled at 128 Hz was used. The dataset was first pre-processed to remove any noise. The signal passed through a Butterworth filter to obtain 0–60 Hz frequency range and an IIR notch filter was implemented at 50 Hz to

remove power-line noise. Segmentation was also performed on the dataset and the data was divided into segments of 60s each.

The signal was further decomposed into 5 levels (D1, D2, D3, D4, D5 and A5 consisting of Noise, Gamma, Beta, Alpha, Theta and Delta sub-bands, respectively). Upon obtaining this information, statistical parameters were calculated for each wavelet sub-band, which were further used as an input to two Machine Learning classifiers. The two classifiers were classical in nature and consisted of an SVM classifier with 'rbf' kernel function and a K-Nearest Neighbours classifier, choosing K value as 6. The classification was performed channel wise in order to determine the best ten channels for the final neural network model. Both models were trained with a subset of the original dataset that consisted of single channel data. The models were then tested for their accuracy scores, using a standard training and testing split of **80:20**. Average of ten accuracies was taken.

The best channels for Alzheimer's Disease were: **EMG, Fp2, Fp1, EKG, A2, PG1, C4, T4, F7, F3**. This can be confirmed since Alzheimer's disease is mainly prevalent in the frontal, temporal and parietal regions of the brain. These channels are mainly present in this region.

In order to combat the drastically smaller size of the new dataset, Data Augmentation was performed for the data from the best ten channels. A GAN network was trained using CTGAN architecture to generate synthetic clones of the dataset with high fidelity. Finally, a dataset which was effectively double in size was obtained.

The last stage of this study included the use of Neural Networks to classify Alzheimer's data. A 1-D CNN model with an LSTM layer was chosen for this task. The CNN model used a 'ReLu' activation function and 'Adam' optimization algorithm. This architecture was trained using both datasets, i.e., before and after data augmentation. The model was trained using a **80:20** training to testing split. The model was also trained for different combinations of batch sizes and epochs, in order to determine the best possible accuracy. Model loss was calculated with the '**Binary Cross Entropy**' parameter and accuracy was calculated using '**Binary Accuracy**' metric. The final accuracy score was an average of ten predictions performed by the model.

Table 3. CNN model accuracy

Type of Dataset	Batch Size	Epochs	Decomposition Level
Pre-CTGAN Dataset	10	150	87.64%
		200	91.90%
		300	86.30%
	100	200	80.54%
Post-CTGAN Dataset	10	200	97.61%

In this paper, a non-invasive and accurate method is proposed for diagnosing Alzheimer's Disease by using EEG signals. The proposed method suggests pre-processing using signal processing techniques, to remove noise from the signal. Further, segmentation and feature extraction were performed on the dataset using Discrete Wavelet Transform and Statistical methods. Classical Machine Learning models of SVM and KNN were used to distinguish the different channels of the dataset and the 10 best channels

were chosen. CTGAN data augmentation was used in order to generate synthetic clones of the data, in order to effectively double the dataset. Finally, a 1-D CNN model with LSTM layer was used as a classifier. The model was trained for various parameters and it was observed that a batch size of **10** and epoch as **200** was ideal for training, without overfitting. It was also deduced that the dataset before data augmentation provides an accuracy of **91.9%** whereas after data augmentation a highest accuracy of **97.61%** was achieved. Table 3 summarizes all the accuracies achieved for the 1-D CNN LSTM model.

The main aim of this work: "To develop an accurate, inexpensive and non-invasive method to diagnose Alzheimer's Disease" was achieved. The study can be further extended to diagnose other mental illnesses such as Seizures, Parkinson's Disease etc. We hope this work acts as a stepping stone for further research with EEG Signals.

6 References

[1] M. V. Karki and S. Yasmeen, "Neural network classification of EEG signal for detection of brain abnormalities," *Lecture Notes in Electrical Engineering*, pp. 308–316, 2018. https://doi.org/10.1007/978-981-10-8240-5_34

[2] S. Yasmeen and M. V. Karki, "Neural network classification of EEG signal for the detection of seizure," 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), 2017. https://doi.org/10.1109/RTEICT.2017.8256658

[3] G. Xu, T. Ren, Y. Chen, and W. Che, "A one-dimensional CNN-LSTM model for epileptic seizure recognition using EEG signal analysis," *Frontiers in Neuroscience*, vol. 14, p. 578126, 2020. Published 2020 Dec 10. https://doi.org/10.3389/fnins.2020.578126

[4] V. C. Bibina, Upasana Chakraborty, R. Mary Lourde, and Ajit Kumar, "Time-Frequency Methods for Diagnosing Alzheimer's Disease Using EEG: A Technical Review." In Proceedings of the 6th International Conference on Bioinformatics and Biomedical Science (ICBBS '17). Association for Computing Machinery, New York, NY, USA, 49–54, 2017. https://doi.org/10.1145/3121138.3121183

[5] C. Lehmann, T. Koenig, V. Jelic, L. Prichep, R. E. John, L. O. Wahlund, Y. Dodge, and T. Dierks, "Application and comparison of classification algorithms for recognition of Alzheimer's disease in electrical brain activity (EEG)," *Journal of Neuroscience Methods*, vol. 161, no. 2, pp. 342–350, 2007. https://doi.org/10.1016/j.jneumeth.2006.10.023

[6] M. Cohen, *Analyzing Neural Time Series Data*. Cambridge (Massachusetts): The MIT Press; 2014. https://doi.org/10.7551/mitpress/9609.001.0001

[7] L. Xu, M. Skoularidou, A. Cuesta-Infante, and K. Veeramachaneni, Modeling Tabular data using Conditional GAN. arXiv.org. https://arxiv.org/abs/1907.00503. Published 2021. Accessed August 13, 2021.

[8] R. Cassani, M. Estarellas, R. San-Martin, F. J. Fraga, and T. H. Falk, "Systematic review on resting-state EEG for Alzheimer's disease diagnosis and progression assessment," *Disease Markers*, 5174815, 2018. https://doi.org/10.1155/2018/5174815

[9] G. Fiscon, E. Weitschek, A. Cialini, G. Felici, P. Bertolazzi, S. De Salvo, A. Bramanti, P. Bramanti, and M. C. De Cola, "Combining EEG signal processing with supervised methods for Alzheimer's patients classification," *BMC Medical Informatics and Decision Making*, vol. 18, no. 1, p. 35, 2018. https://doi.org/10.1186/s12911-018-0613-y

[10] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: A systematic review," *Journal of Neural Engineering*, vol. 16, no. 5, p. 051001, 2019. Published 2019 Aug 14. https://doi.org/10.1088/1741-2552/ab260c

[11] S. L. Oh, J. Vicnesh, E. J. Ciaccio, R. Yuvaraj, and U. R. Acharya, "Deep convolutional neural network model for automated diagnosis of schizophrenia using EEG signals," *Applied Sciences*, vol. 9, no. 14, p. 2870, 2019. https://doi.org/10.3390/app9142870

[12] A. Rizal, W. Priharti, and S. Hadiyoso, "Seizure detection in epileptic EEG using short-time fourier transform and support vector machine," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 17, no. 14, pp. 65–78, 2021. https://doi.org/10.3991/ijoe.v17i14.25889

[13] S. Khan, A. Khan, N. Hameed, M. A. Taufiq, and S. Riaz, "Localizing epileptogenic zone from high density EEG data using machine learning," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 17, no. 6, p. 73, 2021. https://doi.org/10.3991/ijoe.v17i06.18653

[14] K. P. Ayodele, W. O. Ikezogwo, and A. A. Osuntuyi, "Empirical characterization of the temporal dynamics of EEG spectral components," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 16, no. 15, p. 80, 2020. https://doi.org/10.3991/ijoe.v16i15.16663

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