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Analysis of Multichannel Neurophysiological Signal for Identifying Epileptic Cases Using Hybrid Deep-Nets

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Abstract: Neurophysiological parameters revealed by resting-state electroencephalography (rsEEG) may be helpful in the diagnosis of various brain diseases like Epilepsy, Alzheimer's, depressive disorders, and many others. Due to the abrupt onset of seizures, Epilepsy is a chronic nerve illness that interferes with an epileptic patient's regular everyday activities. However, manual investigation of EEG for finding epileptiform discharges by skilled neurologists is a laborious, time-consuming, and error-prone process. It might cause a significant delay in providing clinical care to a person who could have epilepsy. This work offers a straightforward method for analyzing EEG data for the purpose of identifying epileptic features by iteratively simulating multiple deep learning models. It also attempts to include big data analytics for handling the challenge of analyzing the mountain of unstructured EEG data, available and accessible in numerous formats. In contrast to the state-of-the-art works, the performance scores of the proposed methods show significant improvement for the considered assessment parameters. Additionally, after testifying the performance of this proposed technique for relevant datasets, its application can be extended to identify other neurodegenerative disorders as well. Therefore, this study can assist physicians and healthcare professionals in the efficient care and treatment of patients with mental health issues.

Index Terms: Electroencephalogram, Deep Learning, CNN, Cognitive Dysfunction.

1. Introduction

Epilepsy is a severe neurological condition that disrupts the normal functions of the brain, leading to abnormal behavior, lack of sensation, and seizures [1]. A seizure is triggered when there is uncontrolled electrical activity in the brain, which activates an excessive number of cells at the same time. Seizures can be caused by a wide range of underlying medical conditions, including mental and physical illness; an imbalance in the level of sugar or sodium in the blood; withdrawal symptoms from an addiction to alcohol or drugs; a head injury; brain tumors; neurological disorders (ND) such as dementia, Alzheimer's disease (AD), and others [2]. If a person has two seizures that are completely unprovoked and last for at least 24 hours each, that person is advised to go for epilepsy diagnosis. This ailment can cause psychiatric conditions such as anxiety and depression, coupled with cognitive difficulties and social isolation. It may also hurt the patients physically because of the fractures and bruising that are associated with seizures. In addition to that, patients have a risk of premature mortality that is up to three times higher than the normal healthy population. This risk is referred to as "Sudden Unexpected Death in Epilepsy" (SUDEP) [3]. A prompt diagnosis of this medical problem can effectively support the treatment of those patients who do not need the complex medical procedure [4].

Similar to other neurodevelopmental disorders (NDs), the clinical diagnosis of epilepsy also involves a visual detection of abnormal brain activities in the recording of an electroencephalogram (EEG). It captures the vital neural activity that is necessary for the adequate biological arrangement of a healthy human brain, however any specific abnormalities in the recorded brainwaves signifies the presence of any neurodegenerative disorder. EEG data is acquired using multi-sensor set up that captures the brain signals in the form of multivariate time series. So, it inherently consists of temporal variability to provide valuable insights about human mental status. In motor-imaging (MI) EEG, the participants are required to be awake and they should go through any cognitive or sensory simulation tasks during the recording of EEG. However, contrast to that, Resting-state EEG (rsEEG) describes the recorded brainwaves, that are self-generated without any external stimuli or a specific task. Therefore, the resting state is better suited for people who are difficult to instruct, such as children, the elderly, and people with disabilities. Resting state EEG is able to provide valuable information regarding the health status of the human brain, that can be used to detect a variety of illnesses, including Schizophrenia [5], Alzheimer's Disease (AD) [6], Epilepsy [7], Parkinson's Disease (PD) [8], and so on.

The development of artificial intelligence (AI), and its subfields, machine learning (ML), and deep learning (DL) has been of great assistance to the field of healthcare. Researchers are using these methodologies to support clinical practice of epilepsy too, which is one of the oldest and most frequent neurological disorders in the world [9,10]. The information sheet of WHO [4] claims that 70 percent of epileptic patients could eliminate the chance of having a seizure by getting a proper diagnosis and treatment at the appropriate time. Therefore, various researches have utilized different DL methods like convolutional neural network (CNN) [11], long short-term memory (LSTM) [12], and others, for correctly identifying epileptic patients using their EEG recordings. However, the existing methods have not attained absolute accuracy in this classification task despite being computation intensive. Also, most publications use specialized databases in order to predict seizures, as a result, the outcomes of these cutting-edge works depend heavily on the particular EEG dataset. Opposed to such prevailing view in this field, the proposed methodology is applied to two separate datasets, resulting in cross-subject classification. The primary objective of this proposed methodology is to utilize the power of CNN for learning uniform epileptic-related features from EEG of heterogeneous datasets. Additionally, the presented CNN model uses small kernel sizes for categorizing epileptic patients and healthy individuals, which reduces computational costs and weights updation costs during back-propagation. Thus, this research is expected to efficiently learn distinctive patterns of EEG, recorded for normal and diseased person, for facilitating timely identification of suspected cases to eliminate the life-threatening risks and to enhance the quality-of-life of the patients. Contributions of this research can be summarized as:

- The conventional methodologies suffer the challenge of biased outcome because of human involvement. Further, the manual extraction of features may skip unfamiliar important properties of EEG signals for classifying unhealthy subjects. So, involvement of deep learning techniques may effectively support identifying the epilepsy specific traits from the EEG signal by their effective deep representation learning.
- The proposed work exploits the CNN capability of extracting the sample features intelligently without providing a glimpse of its working procedure. Such black-box operational set-up also prohibit any efforts of intrusion during the process imposing high sense of security.
- This paper investigates the possibilities of detecting epilepsy at an early stage to minimize the consequences caused due to delayed diagnosis. The timely and appropriate therapy mitigates the risk of generating other mental and behavioral disorders, impinging financial and psychological burdens on the patients and their family.
- The executional outcome of the presented methodology achieves better performance scores over the existing standard methods, which confirms its effectiveness for the addressed problem.

The organization of this paper is as follows. Section 2 provides a brief investigation of usability of machine learning and deep learning for different neurological disorders (NDs) including epilepsy. The subsequent section 3 discusses the architecture of the proposed methodology, whereas, the experimental details are discussed in section 4. It also explains the datasets LEMON [13] and TUEP [14], commonly used in similar researches. Additionally, this segment also discusses the data preparation steps and their significance. Section 5 lists the results obtained through experimental evaluation and the comparative analysis shows its improved performance over the state of the art work. Finally, the paper concludes in section 6 with emphasizing the need to incorporate such deep learning solutions for improving human mental health.

2. Related Works

This section discusses the findings of notable research works during recent years in the field of automatic prediction of epilepsy using machine learning (ML) and deep learning (DL). Deivasigamani et al. [15] have demonstrated the effect of features extracted from EEG signals to identify them as either focal or non-focal signals and their application in tracing the epileptogenic region in the brain. They decomposed EEG signal using continuous wavelet transform (CWT) for extracting various important features of EEG. These features include bias, entropy, skewness, kurtosis, weight feature, activity feature, complexity feature, and mobility feature, which play a critical role for the epilepsy disease diagnosis process. In another research [16], the authors retrieved EEG features in both the temporal and frequency domains. These features are separately analyzed by applying the T-test and Sequential Forward Floating Selection (SFFS) in order to find the top and most important features that are associated with epileptic seizures. The information is then sent to two different machine learning classifiers known as Support Vector Machine (SVM) and (K-Nearest Neighbor) KNN, and the outcomes of these classifications are analyzed with the k-fold Cross-Validation (CV) methodology. Apart from handling the dynamic nature of EEG recordings, which are acquired in the interest of epileptic subjects, Qureshi et al. [17] have addressed another challenge of automatic epileptic seizure detection for extracting the most representative and distinguishing features. A framework is proposed here that fetches temporal and spectral features from the sub-bands of EEG signal, decomposed using discrete wavelet transform (DWT). Then these parameters are used to improve the classification accuracy of epileptic seizures using fuzzy-based and traditional machine learning algorithms.

These ML based existing automatic seizure detection techniques use traditional signal processing (SP) along with the hand-engineered spectral and temporal features of EEG. This may cause inconsistency in learning the brain wave patterns for identifying seizures occurrences in different EEG dataset. On the other hand, deep learning (DL) automatically encodes hierarchy of features from given dataset, which are more robust and discriminative than hand-designed attributes. Deep convolutional neural networks (CNN) are used by Hossain et al. [18] to extract patient-specific EEG data. These features are important for learning the general structure of a seizure. The suggested model achieves a descent accuracy (98.05%) when applied to a cross-patient EEG dataset, demonstrating that it is less susceptible to fluctuations in the data that was recorded. Expanding the use of CNN, Wagh and Varatharajah [19] have presented an approach for identifying EEGs of patients with NDs versus EEGs of healthy individuals, that utilizes the domain-specific knowledge. They have constructed a brain network using spatial and functional relationships between different brain regions, which is capable to captures the interactions between them. This model learns features from the EEG signals for classifying them into different neurological disease categories with 87.9% accuracy. Tsiouris et al. [20] have introduced another deep learning architecture, Long Short-Term Memory (LSTM), for epileptic seizure prediction using EEG signals. With the assistance of a two-layer LSTM design, the suggested solution exploits the preictal condition that trouble epilepsy patients. For the purpose of seizure prediction, four preictal windows of varying lengths, spanning from fifteen minutes to two hours, are evaluated, and the results show significant performance improvement. In another research, CNN is utilised for the purpose of extracting important EEG features that are used to classify preictal and interictal states [21]. In addition to this, it proposes a channel reduction method that could assist in the production of a portable seizure prediction system that is both effective and efficient. Further, Usman et al. [11] use a CNN model to extract features from EEG segments that are 29 seconds long and are decomposed using empirical mode decomposition. These segments are then used as input to a single-layer LSTM classifier to carry out classification. The performance analysis of this methodology results in 93% sensitivity and a specificity of 92.5%. Another study by Singh et al. [12] offers a two-layer LSTM network model based on spectral feature of multichannel EEG recordings for the automatic prediction of epileptic seizures. The model is built on the idea that spectral features can be broken down into more specific patterns. It motivates the model to use spectral power and mean spectrum amplitude characteristics of the delta, theta, alpha, beta, and gamma bands of the 23-channel EEG spectrum. Additionally, it was discovered that EEG segments with a duration of thirty seconds were helpful for reliable seizure prediction. With an average classification accuracy of 98.14%, an average sensitivity of 98.51%, and an average specificity of 97.78%, the methodology proposed shows to be an effective solution for properly predicting seizures in real time.

The thorough analysis of current seizure prediction approaches reveals the associated limitations like unalike laboratory set up, small-scale instances of recordings, accessibility regulations, and others, which prevent a thorough comparison of the various approaches proposed in related studies. So, only those state of the art (SOTA) methods are compared with the output of the proposed methodology, that either considers somewhat similar datasets or similar configuration of EEG segments.

3. Proposed Framework

The EEG signals capture electrical activities from human brain, that reveal various traits of cognitive state exposing neurological as well as behavioral condition. The presented work makes an effective attempt to identify a person with epilepsy by analyzing their EEG using convolutional neural network.

Let's assume $\chi^{N\times c\times T}$ is an EEG repository, consisting of EEG recordings of epileptic and healthy patients. These N instances of EEG recordings are captured for T time points using c is the number of channels. For representing a single EEG recording, $\chi_i^{c\times T}$ is used, where $i \in \{1, 2, \dots N\}$. Suppose that $f_{(preprocessing)}$ is the set of steps for basic processing of EEG signal as given in Algorithm 1, *s.t.* $f_{(preprocessing)}\colon \sum_{i=1}^{N} \chi_i^{c\times T} \rightarrow \sum_{i=1}^{N} X_i^{c\times T}$, X_i represents the updated scores of T time steps for all c channels of i^{th} recording, with $i \in [1, N]$. After these primitive processing steps, one dimensional CNN, a deep learning model, is utilized to learn the relevant features of brainwaves symbolizing the epilepsy disease.

Algorithm 1: Steps of EEG preprocessing ($f_{(preprocessing)}$)

Input: $\chi^{N\times c\times T}$, f_s, l_{freq}, h_{freq}, f_n
Output: $X^{N\times c\times T}$

Initialize $X = [\ \ ]$
for i = 1 to N do
X' = Resample the $\chi_i{}^{c\times T}$ by f_s
X' = Application of bandpass filter on X' having frequency range (l_{freq}, h_{freq})
X' = Removing power line noise from the filtered signal X' at f_n
Append X' to list X
End for
Return $X^{N\times c\times T}$

3.1. Methodology

The deep learning architecture presented in this research for classifying normal and diseased EEG signals is shown in Fig. 1. This CNN model requires EEG signals of normal as well as epileptic EEG for training after processing them using the steps mentioned in Algorithm 1. These preprocessed EEG instances are associated with temporal continuity, which is segmented into consecutive equidistant slices, having no overlapping in between. So, $\forall X_i^{c\times T} \in X$ is divided into t sized slots generating ${x_i}_j^{c\times t}$. Here, $(i, j) \in Z: 1 \leq i \leq N$, and $1 \leq j \leq n$, with n representing the number of 2D windows holding the condition $(n \times t = T)$. These EEG segments are adjacent to each other that helps in performing analysis, which are event-independent. As given in Eq. (1), the EEG windows x′ belongs to an epileptic person, if it is marked with label 1, otherwise the segments are assigned label 0 and represents the samples of normal person.

$$\forall x' \in \sum_{i=1}^{N} \sum_{j=1}^{n} {x_i}_j{}^{c\times t} \quad (1)$$

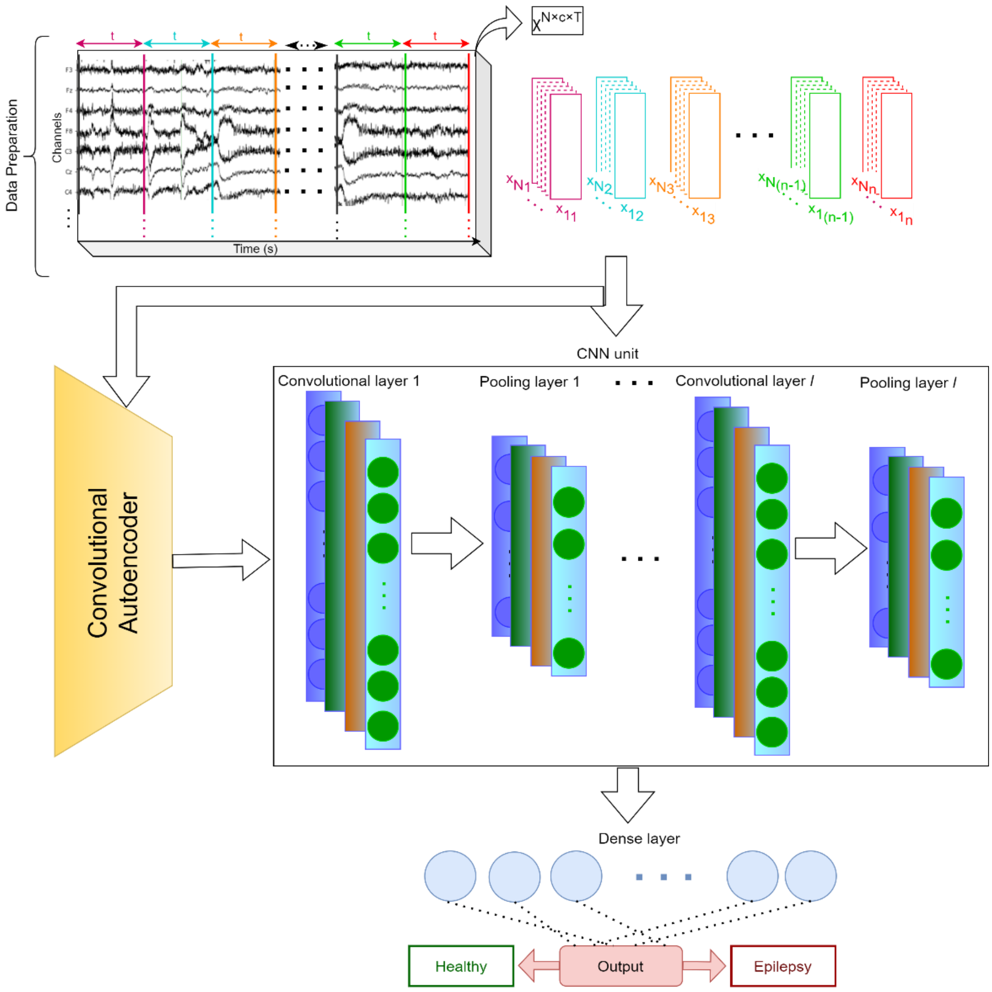


Fig. 1. Architecture of the proposed framework.

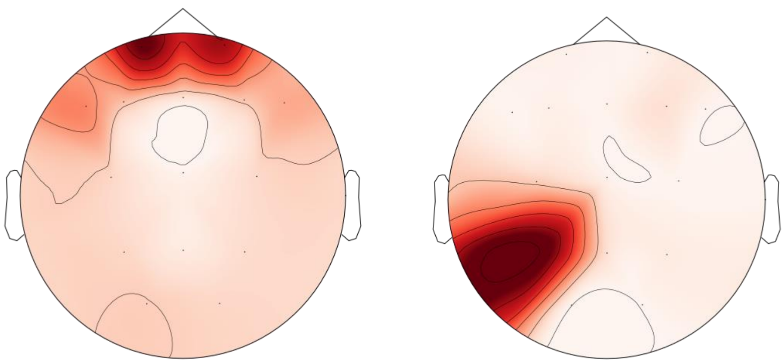
CNN structure imitates the complexity of network structure of human mind and uses backpropagation as well as gradient descent optimization algorithm for learning the distinct patterns of different classes. For extracting features from the input data, it uses a series of filtering, normalization, and nonlinear activation operations. While the input layer is a passive layer that receives the raw 1D data, a small portion of these input neurons, referred to as the convolutional window, are connected to each neuron in the first hidden layer of the CNN. Convolutional layers can be thought of as feature extractors, whereas, pooling layers reduces the dimensionality of a given feature vectors along with careful selection of prominent features. Thus, it helps to eliminate model overfitting by managing the dimensionality of the convolution output. Then, flatten concatenates the output from the convolution layers to form a flat structure, which is fed to multilayer perceptron (MLP) layer. This layer is a fully connected neural network (FCNN) having output neurons equal to the number of classes of classification task, that gives final results. So, this binary classification task uses CNN layers to “learn to extract” by processing the raw 1D EEG slices and utilizes FCNN layers for classification. This can be seen as a combined effort of feature extraction and classification tasks to increase the performance of this prediction assignment.

Apart from finely-tuned vanilla variant of CNN, the presented work attempts to enhance the model efficiency by integrating a CNN autoencoder (CNN-AE) on top of this 1D-CNN model. The autoencoder is trained to reconstruct the input data from a compressed representation learned by the encoder, and in doing so, it learns to extract and represent the most salient and informative features of the data. This CNN-AE can be particularly beneficial to learn more robust and discriminative features from the EEG data which are high-dimensional and complex in nature. The learned representation can then be used as input to downstream tasks like classification, improve the performance of the model. This amalgamation of CNN-AE with 1D CNN proves to be an effective architecture for EEG-based epilepsy analysis due to its ability to model non-linear relationships between the compressed feature set of EEG segments along with reduced risk of model overfitting.

The traditional approach of using a simple hold-out split method prevents the optimal utilization of the training data. K-Fold Cross-Validation (CV) addresses this matter by dividing the entire dataset into K equally sized parts, each of which are distinctly provided for model learning. So, during the process, (k-1) fold is provided to the model as input to perform convolutions and pooling operation. The only operation incurring substantial cost in 1D-CNN model is a series of 1D convolutions, which are just the summing of two 1D arrays with linear weights, resulting in low computational complexity. The subsequent sections provide the details regarding performance of proposed approach, which is significantly improved over the state-of-the-art work.

4. Experimental Details

Elementary requirement for carrying out the model execution is relevant sets of EEG data. This paper considers TUEP EEG recordings stored under ``Epilepsy" directory as “unhealthy” and Lemon EEGs as “healthy”. Fig. 2 shows topomap (popular term for topographic maps) of EEG for both classes. Topographic maps are a way of visualizing the distribution of electrical activity across the scalp in EEG data. As shown in Fig. 2(a), the healthy individuals typically show a more even distribution of electrical activity across the scalp map, whereas the epilepsy patients have abnormal electrical activity, localized to certain areas of the brain. It can be observed as a cluster of red in the topomap, shown in Fig. 2(b). This work aims to achieve best possible classification accuracy for distinguishing healthy and epileptic patients. The following subsections explains the datasets and process of data preparation for the sake of experimental design.



(a) Healthy person (b) Epileptic person

Fig. 2. Architecture of the proposed framework.

4.1. Dataset Description

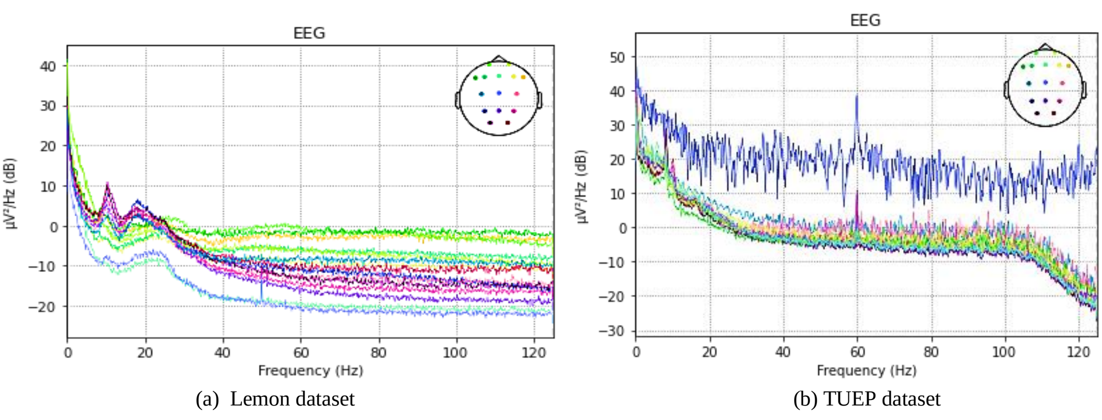
The TUH EEG corpus is created by Temple University founded Neural Engineering Data Consortium (NEDC) in 2010 to support research in neuroscience domain by collecting, categorizing, and de-identifying tens of thousands of archival EEGs. The corpus consists of EEG signal, stored in European Data Format (EDF), paired with the reports written by the attending neurologist for each data file. The naming structure of the files contain fundamental metadata information about every patient session, such as database name, the release version, patient number, session number and date of recording. The repository is freely accessible after putting legitimate request through web portal. This paper has utilized selective subset of EEG corpus, TUH EEG Epilepsy Corpus (TUEP), that contains 100 EEG recordings of epileptic subjects and 100 EEG recordings of normal subjects as determined by a certified neurologist [14].

Another EEG dataset LEMON is released by Max Planck Institute for Human Cognitive and Brain Sciences (MPI CBS), Leipzig, Germany in 2019 [13]. The purpose of this dataset is to relate cognitive and emotional traits with physiological characteristics of brain and body. Data was acquired in four rounds and took almost two years to complete, starting from 2013 to September 2015. It contains resting-state recordings from 216 healthy participants having two logical age groups: young and old. This online repository consists of raw EEG data as well as preprocessed data for all the participants. The raw data is stored in Brainvision data format, which consists of three files: (a) a text header file (.vhdr) containing meta data, (b) a text marker file (.vmrk) containing information about events in the data, (c) a binary data file (.eeg) containing the voltage values of the EEG. On the other side, preprocessed EEG files are stored in EEGLAB file format for eyes-closed (EC) and eyes-open (EO) conditions separately. Each of these consists of two files: (a) float data file (.fdt) containing raw EEG data, and (b) a Matlab file (.set) containing metadata such as number of channels, sampling frequency etc. The methodology proposed in this paper applies very few preprocessing steps on raw EEG signals, retrieved from the two above mentioned repositories. Their details are briefly summarized further in the subsequent subsections.

4.2. Channel selection

EEG data of healthy individuals, fetched from LEMON dataset, are recorded using a 10-10 system (extended localization of standard 10–20 montage) with 62-channel. Whereas, TUEP dataset, which has records of epilepsy patient, uses 10-20 system with 30 channels. The Lemon EEG contains one ‘EOG’ (Electrooculogram) channel ‘VEOG’ to study eye movement, which is not attached to the EEG cap. Further, the TUEP recording also has seven channels not connected to the scalp. It consists of one `ECG' (Electrocardiogram) channel ‘EEG EKG1-REF’ to monitor cardiac activity and one channel ‘PHOTIC-REF’ to investigate the brain status due to photic stimulation. Also, purpose of other five channels, ‘EEG ROC-REF’, ‘EEG LOC-REF’, ‘IBI’, ‘BURSTS’, and ‘SUPPR’ are not known in the context of experimental usage. So, such channels are excluded in this study. The hemisphere and lobe related information for rest electrodes of EEG recordings, fetched from both datasets, are given in Table 1.

It is evident from this listing that channel labels of TUEP are manipulated by the recording institution and not synchronized with standard naming system. So, they are renamed as per the standard 10-20 montage naming structure. Then, subset of common channels is selected from the healthy and patient populations, resulting in elimination of incompatible electrodes. This selection results in fifteen channels symmetrically available in both datasets. The power spectral analysis with the selective number of channels is shown in Fig. 3 for single subject belonging to each dataset, which provides valuable insights into the frequency characteristics for respective EEG signals. It can be easily observed that the power spectral density (PSD) plot of epileptic person tends to have increased power in the delta (0.5-4 Hz) and theta (4-8 Hz) frequency bands, and decreased power in the alpha (8-12 Hz) and beta (12-30 Hz) frequency bands, compared to healthy individuals.



(a) Lemon dataset (b) TUEP dataset

Fig. 3. Power spectral density plot of single EEG recording fetched from the EEG repositories of healthy person (LEMON) and epilepsy patients (TUEP).

Table 1. Type Sizes for Camera-Ready Papers

Position	Lobes	Lemon Channel Labels	TUEP Channel Labels
Left hemisphere	Frontal	F1, F3, F5, F7	EEG F3-REF, EEG F7-REF
Right hemisphere	Frontal	F2, F4, F6, F8	EEG F4-REF, EEG F8-REF
Midsagittal line	Frontal	Fz	EEG FZ-REF
Left hemisphere	Prefrontal	Fp1	EEG FP1-REF
Right hemisphere	Prefrontal	Fp2	EEG FP2-REF
Left hemisphere	Temporal	T7	EEG T1-REF, EEG T3-REF, EEG T5-REF
Right hemisphere	Temporal	T8	EEG T2-REF, EEG T4-REF, EEG T6-REF
Left hemisphere	Frontotemporal	FT7	None
Right hemisphere	Frontotemporal	FT8	None
Left hemisphere	Central	C1, C3, C5	EEG C3-REF
Right hemisphere	Central	C2, C4, C6	EEG C4-REF
Midsagittal line	Central	Cz	EEG CZ-REF
Left hemisphere	Frontocentral	FC1, FC3, FC5	None
Right hemisphere	Frontocentral	FC2, FC4, FC6	None
Left hemisphere	Parietal	P1, P3, P5, P7	EEG P3-REF
Right hemisphere	Parietal	P2, P4, P6, P8	EEG P4-REF
Midsagittal line	Parietal	Pz	PZ-REF
Left hemisphere	Centroparietal	CP1, CP3, CP5	None
Right hemisphere	Centroparietal	CP2, CP4, CP6	None
Midsagittal line	Centroparietal	CPz	None
Left hemisphere	Occipital	O1	EEG O1-REF
Right hemisphere	Occipital	O2	EEG O2-REF
Midsagittal line	Occipital	Oz	None
Left hemisphere	ParietoOccipital	PO3, PO7, PO9	None
Right hemisphere	ParietoOccipital	PO4, PO8, PO10	None
Midsagittal line	ParietoOccipital	POz	None
Left hemisphere	Posterior temporal	TP7	None
Right hemisphere	Posterior temporal	TP8	None
Left hemisphere	Mastoid Process	None	EEG A1-REF
Right hemisphere	Mastoid Process	None	EEG A2-REF
Left hemisphere	Anterior frontal	AF3, AF7	None
Right hemisphere	Anterior frontal	AF4, AF8	None
Midsagittal line	Anterior frontal	AFz	None

4.3. Data Preprocessing

A collective summary of necessary operational steps for data preparation is given in Fig. 4. The left part of the diagram concerns with epileptic EEG preprocessing and right part, on the other side, deals with healthy EEG data. The first half of the image starts with identification of matching electrode-pairs from the topography of EEG repositories considered here. After establishing common set of electrodes for the EEG signals fetched from both datasets, they have been nominally preprocessed with basic steps like downsampling and filtering. The sampling frequency of EEG fetched from LEMON is 2500 Hz, whereas for TUEP, it is 250 Hz. Then all the steps mentioned in Algorithm 1 is applied on the raw signals. The highest frequency band of EEG considered by this paper is $\mathrm{B} = 125$ Hz, which requires sampling rate of $\mathrm{f_s} = 2\mathrm{B}$ i.e., 250Hz according to Nyquist theorem [22]. All EEG signals $\sum_{\mathrm{i=1}}^{\mathrm{N}} \chi_{\mathrm{i}}^{\mathrm{c,T}}$ are downsampled by $\mathrm{f_s}$. The resultant signal is then processed to remove electrical noise or artifacts with the help of filters for producing interpretable clinical EEG tracing. These filters are divided into two classes: FIR (Finite Impulse Response) and IIR (Infinite Impulse Response) based on the coefficients $\mathrm{b_k}$ and $\mathrm{a_k}$ of Eq. (2). This equation represents input-output relationship between $x(r)$ and $y(r)$, where $\forall b_i \in b_k$ get multiplied by the previous input values i.e., $x(r-i)$, and $\forall a_i \in a_k$ get multiplied by the previous output values i.e. $y(r-i)$. The IIR filters depend on previous inputs and outputs both, whereas, the FIR filters have $a_k = 0,\ \forall k \in \{1,2, \ldots Z\}$. So, each output value of $y(r)$ depends only on the J previous input values as Eq. (2) transforms to $y(r) = \sum_{k=0}^{J} b_k x(n-k)$, J revealing the order or length of the filter.

$$\begin{aligned} y(r) &= b_0 x(r) + b_1 x(r-1) + \cdots + b_J x(r-J) \\ &\quad - a_1 y(r-1) - a_2 y(r-2) - \cdots - a_Z y(r-Z) \\ &= \sum_{k=0}^{J} b_k x(r-k) - \sum_{k=1}^{Z} a_k y(r-k) \end{aligned} \tag{2}$$

In clinical EEG, low-pass filters (LPF), high-pass filters (HPF), and notch filters are applied for cleaning the EEG waveforms for better Interpretability. The presented work uses all except the first type (LPF) to improve the signal to noise ratio (SNR) of downsampled EEGs by differentiating between spectra of noise and target. Here, a high-pass filter is used to remove slow fluctuations or direct current (DC) component, and, a notch filter at 50 Hz attenuates power line components [23]. Application of these steps produces $\mathrm{X}^{\mathrm{N \times c \times T}}$. For the ease of analysis, Fig. 4 displays the plot of single channel only to reflect the transformation due to the mentioned basic preprocessing steps. However, all the selected channels of the EEG signals picked for this experimental analysis go through same processing. Then later half of this figure visualizes the image map of 25 seconds windows generated from the processed channel signals. Such equal duration chunks are created for every channel of all EEG files selected for proposed analysis, and are also termed as epochs.

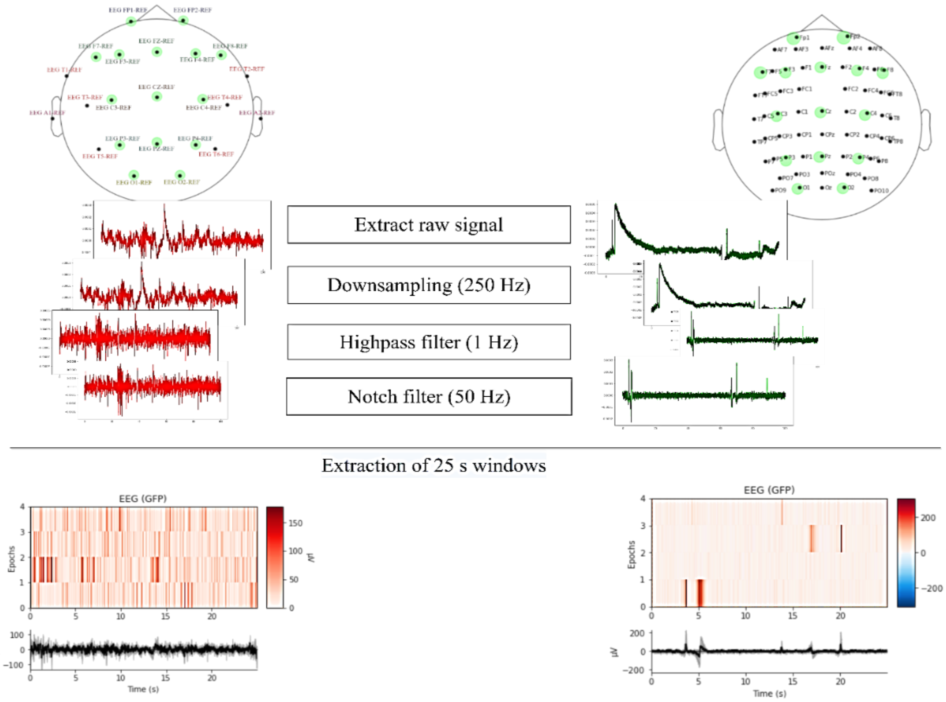


Fig. 4. Steps of epoch preparation from EEG recordings.

4.4. *Windowing*

The presented methodology has used the non-overlapping contiguous time windows of 25 seconds to train the deep learning model for better classification score of epileptic EEG. So, as mentioned in preceding Section 3, $\forall X_i^{c\times T} \in X^{N\times c\times T}$ is divided into $t = 25$ sized slots generating $\sum_{i=1}^{N}\sum_{j=1}^{n} x_{i_j}^{c\times t}$, n denoting the total number of chunks fetched from i^{th} EEG recording and $c = 15$, is the number of channels picked up for experimental analysis. Let's say, $\omega = \{\omega_1, \omega_2, \dots, \omega_{N\times n}\}$ is a set of windows representing all epochs given by x_{i_j}. $\forall \omega_i \in$ is a two-dimensional matrix with dimension $(c \times t)$.

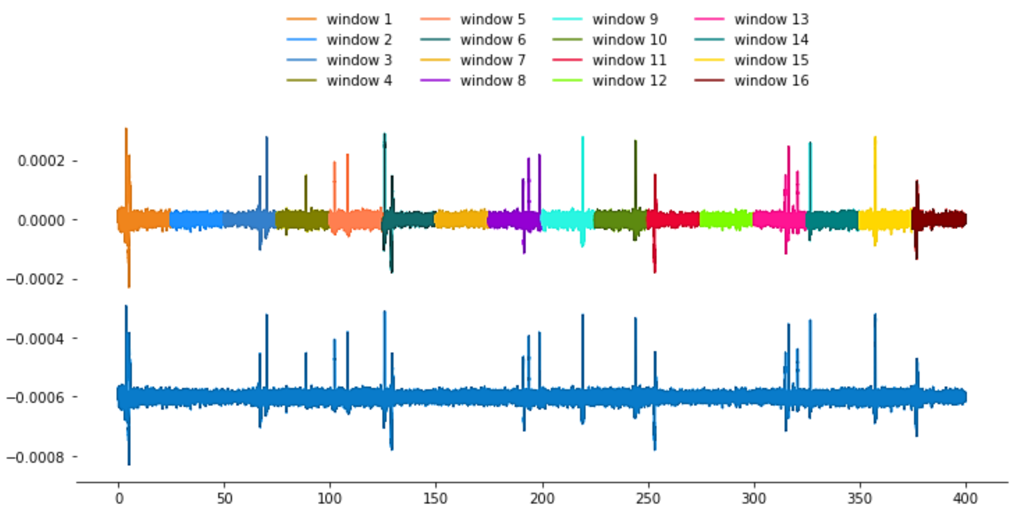


Fig. 5. Windows generation from a single EEG channel.

Fig. 5 shows some windows created from the same channel, which is used earlier to demonstrate the preprocessing steps of. The lower plot with a uniform color represents the channel signal, whereas the upper plot with different color codes denotes all possible windows generated from that channel. These windows are assumed to be independent of each other, even if they belong to same recording. These windows enable the suggested CNN architecture to learn the EEG features intelligently and efficiently, in order to classify the healthy and epileptic person.

5. Results and Discussions

The results of this presented methodology are evaluated using two separate EEG repository, TUEP and LEMON, respectively consisting of EEG recordings of epileptic patients and healthy person. To avoid overworking of resources, instead of whole instances, 24 epileptic and 28 healthy EEG recordings are selected from these repositories. For labeling purpose, recording of healthy subjects are assigned 0 and that of diseased are set as 1. Performance of CNN relies on the quantum of dataset used for training the model, which pilots the segmentation of every recording with their labels same as the parent flag. This slicing considers applying 25s window on the preprocessed EEG signals, generating 2648 EEG samples, that includes 1491 Epileptic and 1157 normal chunks of EEG. Before feeding these data to the deep neural network, scaling is done for faster training and convergence. There are two techniques of feature scaling, Normalization and Standardization, whose effect is shown in Fig. 6 for a single window of all 15 channels, selected for this experiment.

The presented work considers the first one as it has minimum outliers, even visible in the given diagram. Additionally, the EEG signals are non-Gaussian, so, normalization is more suitable here and they are scaled in the range of [0, 1]. $\forall c_k \in c, \sum_{i=1}^{N\times n} \omega_i^{c_k \times t}$ is transformed to generate the features $\sum_{i=1}^{N\times n} \omega'^{(c_k\times t)}_i$, as per the standard equation, $\omega'_i = \left(\omega_i - \omega_{i_{(min)}}\right) / \left(\omega_{i_{(max)}} - \omega_{i_{(min)}}\right)$. Here, $\forall c_k, k \in [1,15]$, ω_i is a single window having dimension $1 \times t$, $\omega_{i_{(min)}}$ represents the minimum value of this window, $\omega_{i_{(max)}}$ denoting maximum value and ω' is the transformed t sized vector. These windows are fed to the deep learning model presented in this paper for identifying the healthy and epilepsy instances.

The proposed framework explained in preceding Section 3 is fixed on the basis of various experiments with different configuration of 1D CNN. In the context of the problem addressed by this paper, results of two vanillas CNN and one stacked-CNN are found to be worthy enough for discussion, as they deliver comparable scores as their output. For the ease of reference, the vanilla variant of CNN is assigned coded representation: *Model A* and *Model B*, whereas, *Dual CNN* is used for stacked-CNN. Fig. 7 provides a brief overview about the layered structures of each deep neural network, used for experimental purpose. After evaluating outcomes of various executions, the number of layers, number of filters, their sizes, etc., is decided. Different pooling operations applied to the model are Max pooling, Average pooling, Global Average pooling. Non-linear activation functions, such as, ReLu, Leaky ReLu, Softmax, and Sigmoid are used to learn complex mappings and to avoid the vanishing gradient problem. Varying length of strides is used in different layers of presented 1D CNN including 1, 2, and 3. Dropouts help in preventing overfitting which memorizes the inputs instead of learning general traits of the inputs. Although, the optimal value of dropout is suggested as 0.5, this experiment also considers dropout rate of 0.1 and 0.2 too. Binary cross entropy is the loss function that assesses the deviation in the predicted output from the target output. The optimizer adopted here is Adam algorithm, which updates the weights and bias through the backpropagation algorithm, and tries to minimize the loss function. The *model A* can be seen to have five convolutional layers, and it uses two pooling operations, max pooling and average pooling, during learning phase to downsample the feature map, whereas, global average pooling layer is applied to facilitate the flattening of feature map. The kernel size used by CNN layers are 3, and the pooling size is chosen to be 2. This model configuration uses rectified linear unit (ReLu), leaky ReLu, and softamx activations at different layers, and dropout rate of 0.5 is found to be best suited here. *Model B* consists of four CNN layers with filter sizes of 5 and 3, and ReLu activation function. The layers are also regularized with spatial dropout to randomly drop out 10% to 50% of the feature maps at various layers. To feed the generated feature map to a dense layer having 64 neurons, global max pooling is used to fetch the maximum value over each of the 256 feature maps to produce a single vector of size 256. Similar to these two vanilla CNN, the *Dual CNN* model also accepts EEG segments of shape (6250, 15) which represents a time series of 6250 timesteps with 15 features per timestep. This model consists of a series of convolutional layers with varying kernel sizes and activation functions, followed by max pooling and dropout layers. The output of these layers is fed into a dense layer with 64 units and ReLU activation function, followed by another dropout layer. This defines a base model that provides encoded representation of EEG features, which is further passed to a CNN network for classification purpose.

For validating these models, the available set of data is divided into training and validation set. Instead of vanilla distribution method of train-test split, K-Fold cross-validation is used to obtain unbiased performance of the model. Here, value of K is chosen to be 5, resulting in five non overlapping folds of the given dataset. Fig. 8 shows the comparative graph plot for accuracy and loss for training and validation set during each epoch of model learning. Different model configurations are assigned different color code for better interpretations of the results. Here the convergence rate of model A (Vanilla CNN) and Dual CNN for validation set show similar pattern of accuracy and loss curve plotted during training. This eliminates any possibility of model overfitting and confirms the reliability of the result. The plot of loss for Dual-CNN is also found to be decreasing with every epoch, which guarantees obtaining minimum error value during further training of the model, whereas model A seems to be a victim of overfitting.

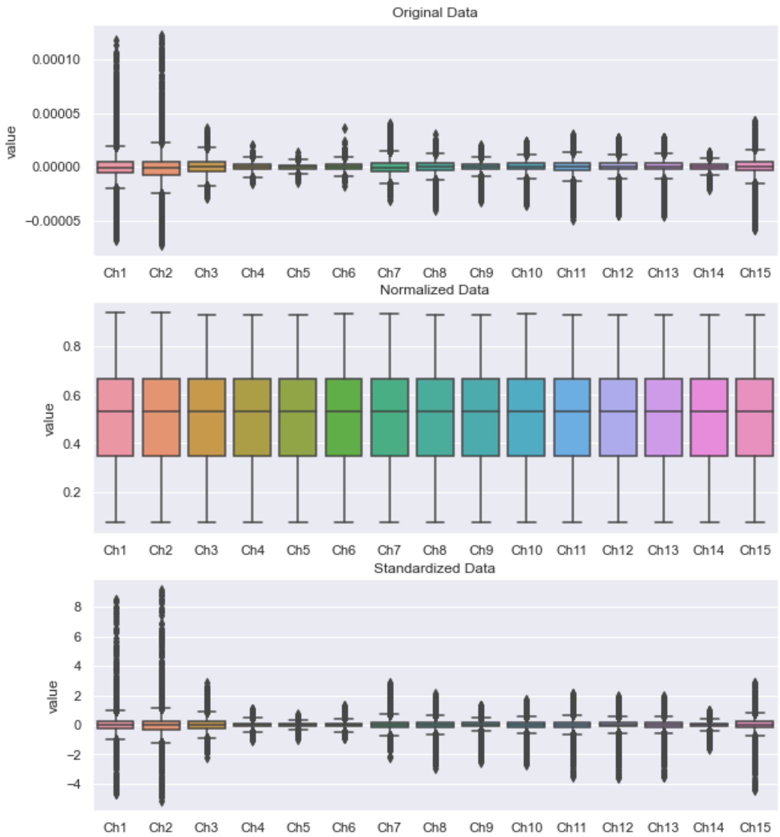
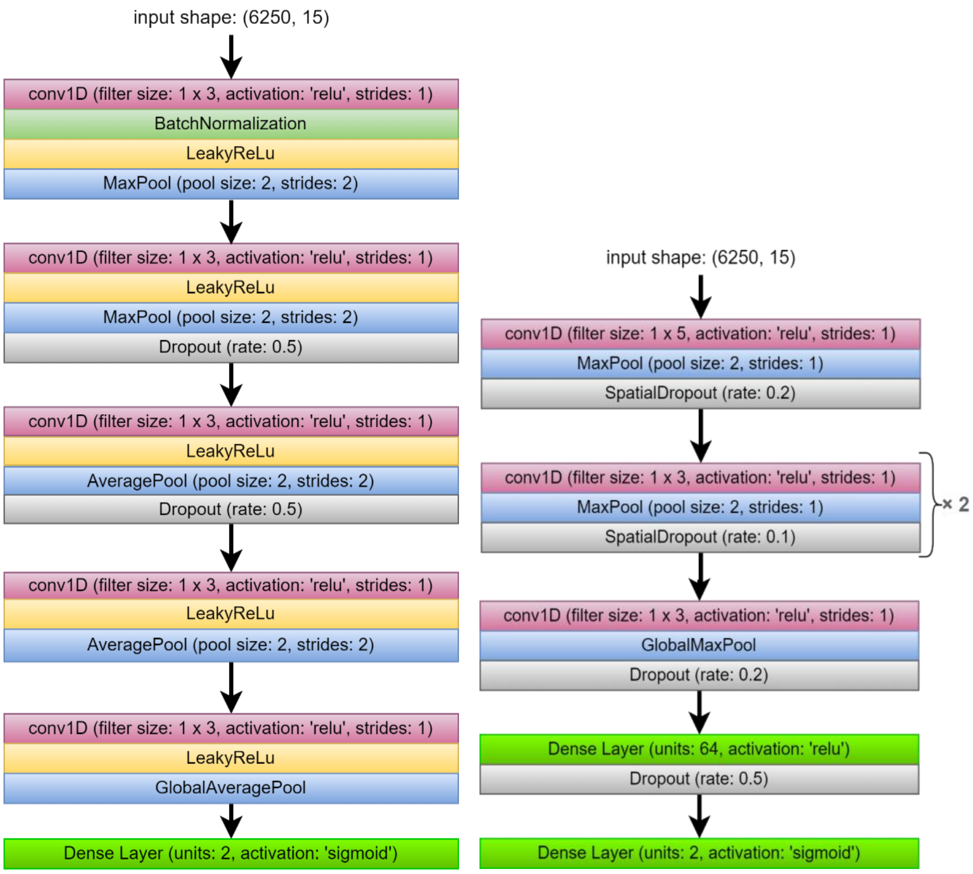
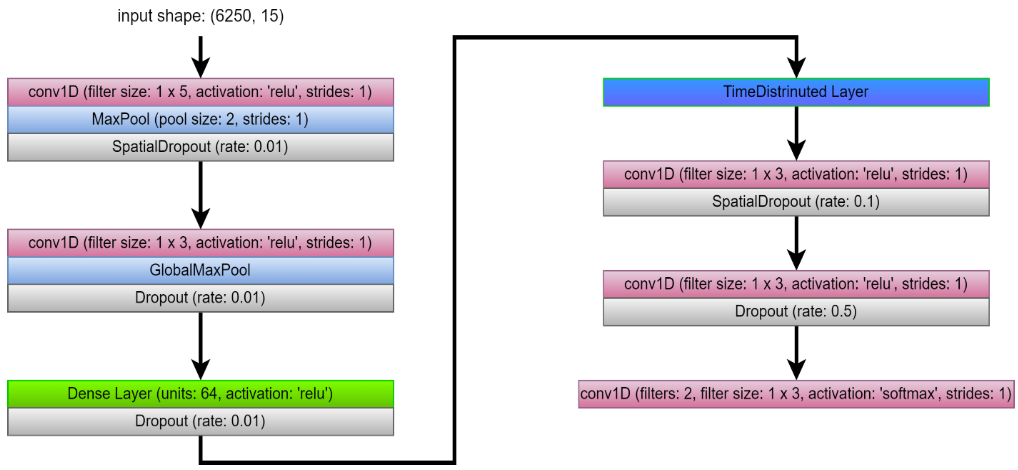


Fig. 6. Effect of scaling on EEG segments.



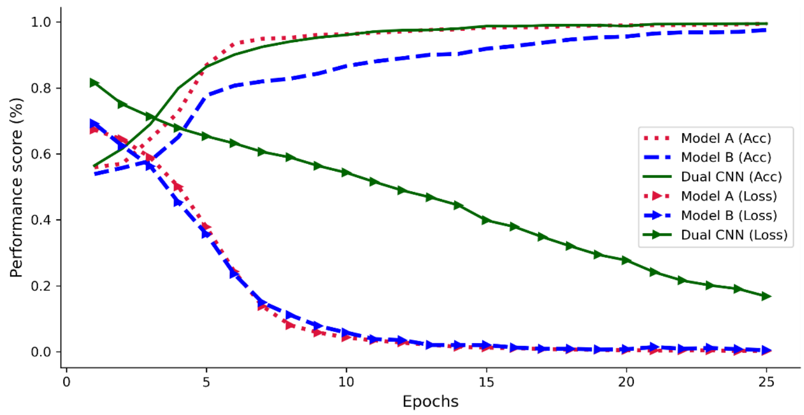
(a) Model A (Vanilla CNN) (b) Model B (Vanilla CNN)



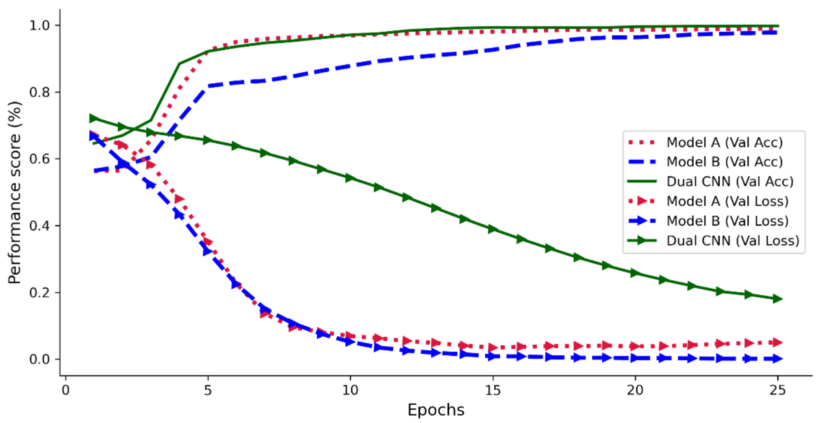
(c) Dual CNN

Fig. 7. Architectural description of all CNN models exploited for the proposed framework.

Additional assessment of these two suggested deep learning architectures includes their training evaluation for four distinct batch sizes 32, 64, 128 and 256. All the recorded learning results are analyzed using a set of standard performance metrics, whose mathematical equations are given further in this section. For the sake of understanding the terms used in these equations, let’s assume that healthy EEG samples are assumed as positive whereas epileptic EEG are taken as negative. Eq. (3) calculates accuracy of the model as the number of correct predictions out of total count of predictions. Another metric precision is calculated as the given Eq. (4). It is ratio between the count of correctly predicted positive samples to the total number of samples classified as positive (either correctly or incorrectly). On the other hand, recall is related to the model's ability to detect Positive samples only and also referred to as true positive rate (TPR). As per the Eq. (5), it is the proportion of number of accurately classified positive samples out of total positive samples. F1-Score, which is calculated in Eq. (6), gives a collective idea about precision and recall as it computes harmonic mean of both.



(a) Training performance



(b) Validation performance

Fig. 8. Plot of training performance and validation performance of the identified deep learning models.

$$Accuracy = \frac{True_{pos.}+True_{neg.}}{True_{pos.}+False_{pos.}+True_{neg.}+False_{neg.}} \times 100 \tag{3}$$

$$Precision = \frac{True_{pos.}}{True_{pos.}+False_{pos.}} \times 100 \tag{4}$$

$$Sensitivity(Recall) = \frac{True_{pos.}}{True_{pos.}+False_{neg.}} \times 100 \tag{5}$$

$$\mathrm{F1-Score} = 2 \times \frac{\{\mathrm{Precision} \times \mathrm{Recall}\}}{\mathrm{Precision}+\mathrm{Recall}} \tag{6}$$

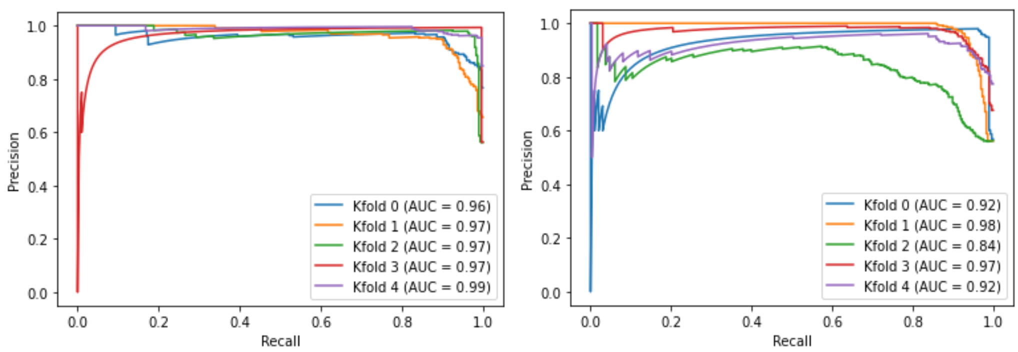
$$Specificity = \frac{True_{neg.}}{True_{neg.}+False_{pos.}} \times 100 \tag{7}$$

These performance metrics have used four key terms $\{\mathrm{True_{pos.}}, \mathrm{False_{pos.}}, \mathrm{True_{neg.}}, \mathrm{False_{neg.}}\}$. Following is their interpretation in the context of classifying EEG signals of healthy and epileptic person:

- $\mathrm{True_{pos.}}$: This specifies the correct predictions of the model for EEG windows of healthy people from the given validation set that includes EEG signal windows of epileptic patients too.
- $\mathrm{False_{pos.}}$: It represents the number of epileptic patients incorrectly classified as healthy people by the model.
- $\mathrm{True_{neg.}}$: This is the count of non-healthy people correctly identified as epileptic according to the model prediction.
- $\mathrm{False_{neg.}}$: For all the EEG windows of epileptic patients, it states the count of incorrectly predicting them as healthy EEG windows by the model.

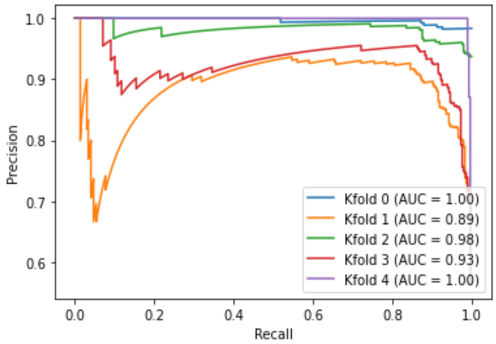
Fig. 9 represents the plot of precision and recall for each fold of all four batch sizes for evaluating the vanilla CNN model, whereas Fig. 10 shows the same performance analysis for Dual-CNN. A precision-recall (PR) curve is a graphical plot of the performance of a binary classifier algorithm. A perfect classifier would have a precision of 1.0 and a recall of 1.0, which would result in a point at the top right corner of the PR curve. A random classifier would result in a diagonal line from the bottom left to the top right of the curve. The area under the PR curve (AUC-PR) is often used as a performance metric for binary classifiers, with a higher AUC-PR indicating better classifier performance.

In order to validate the model performance for this classification task that is concerned with brain health of human, one more important performance measure is used, called receiver operating characteristics (ROC) curve. It plots true positive rate (TPR) against false positive rate (FPR), where FPR is calculated as $(1 - \mathrm{Specificity})$. Eq. (7) represents the mathematical equation, also called true negative rate (TNR), and is complete opposite to sensitivity, given in Eq (5). Specificity assesses the proportion of correctly identified negative samples out of total negative samples. The area under the ROC curve serves as a summary metric for evaluating the performance of a binary classification model. This metric, known as the AUC, quantifies the ability of the model to distinguish between positive and negative examples. A model with an AUC of 0.5, represented by a diagonal line, indicates random guessing and provides a threshold for comparison. Higher AUC values indicate better discrimination between classes.

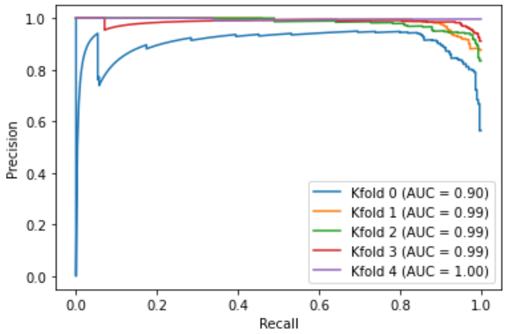


(a) Batch size: 32

(b) Batch size: 64

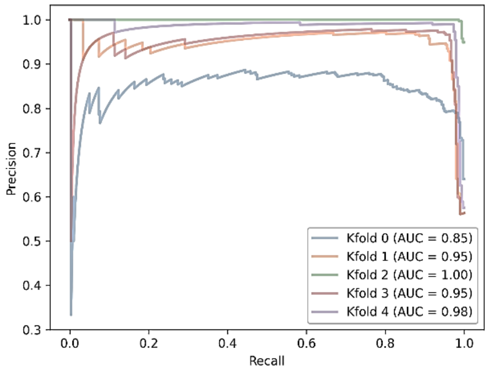


(c) Batch size: 128

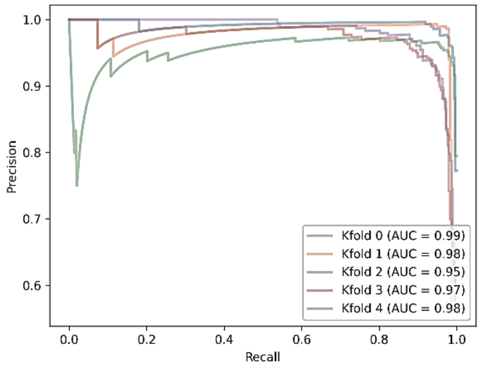


(d) Batch size: 256

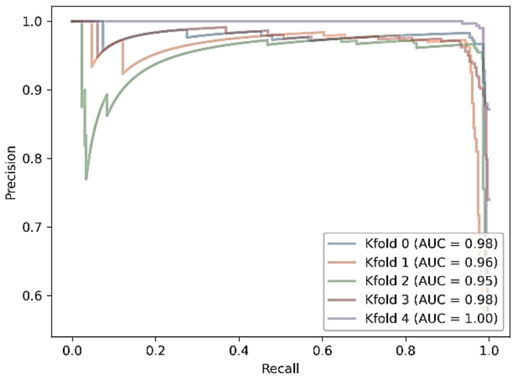
Fig. 9. Precision-Recall curve for vanilla CNN for different batch sizes.



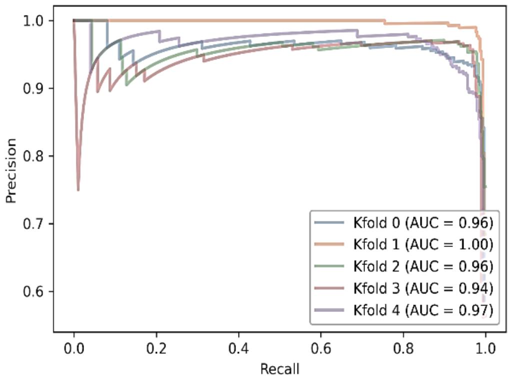
(a) Batch size: 32



(b) Batch size: 64

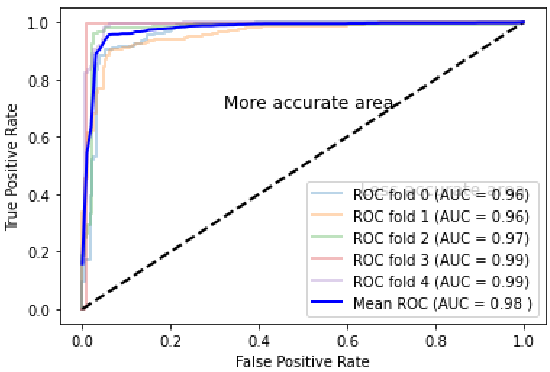


(c) Batch size: 128

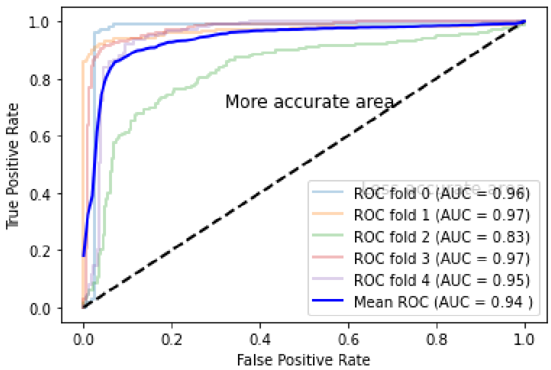


(d) Batch size: 256

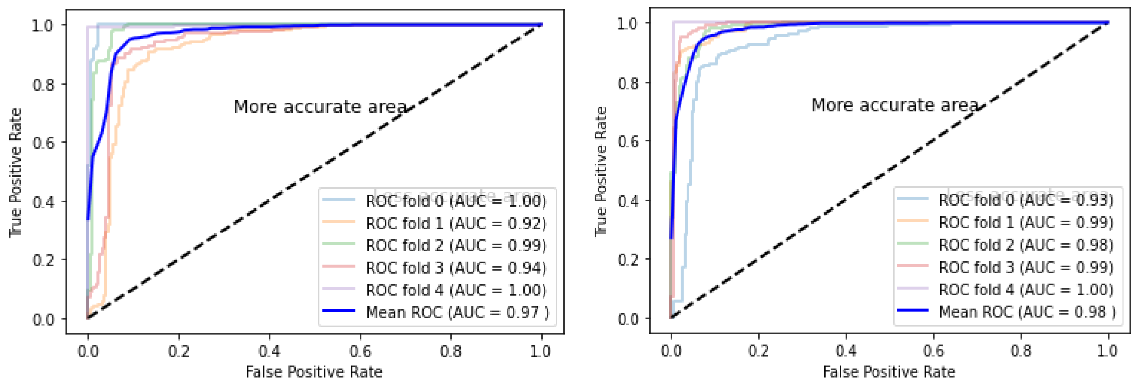
Fig. 10. Precision-Recall curve for Dual-CNN model for different batch sizes.



(a) Batch size: 32



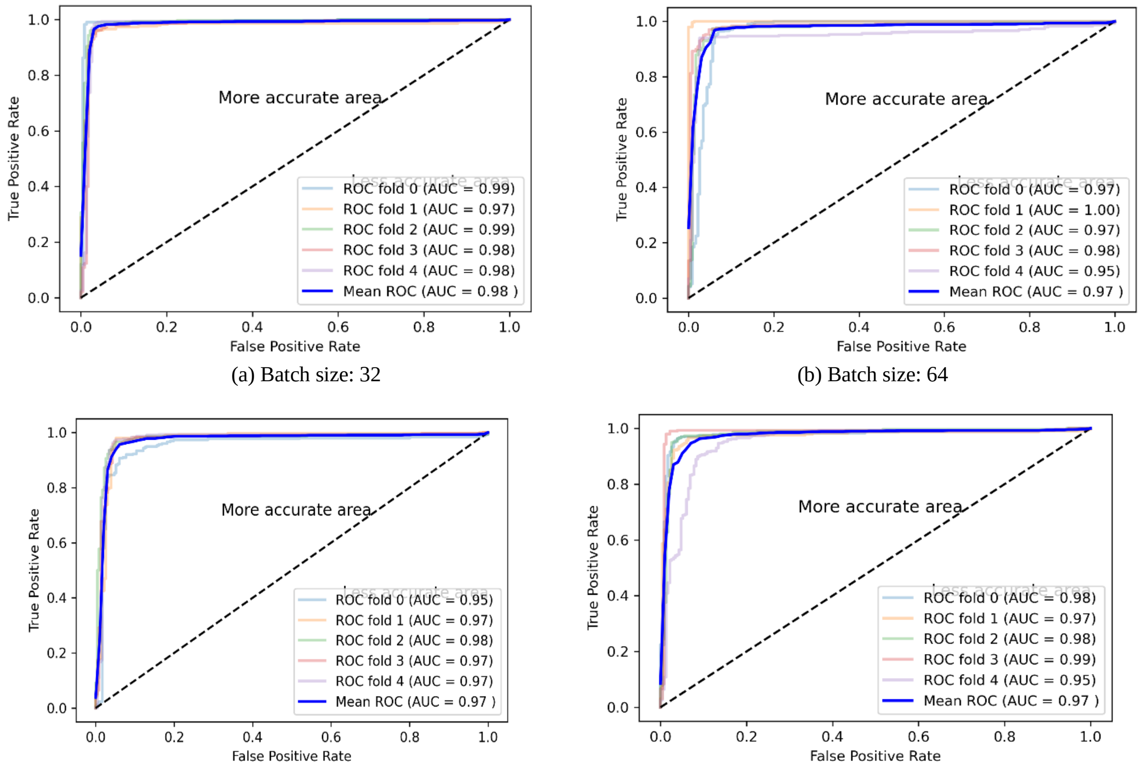
(b) Batch size: 64



(c) Batch size: 128

(d) Batch size: 256

Fig. 11. Mean ROC curves of vanilla CNN model for different batch sizes.



(a) Batch size: 32

(b) Batch size: 64

(c) Batch size: 128

(d) Batch size: 256

Fig. 12. Mean ROC curve of Dual-CNN for different batch sizes.

Fig. 11 and Fig. 12 specifically represent ROC curve for the two models, which plots the true positive rate against the false positive rate for this medical diagnostic binary classification task. A perfect classifier would have a TPR of 1.0 and an FPR of 0.0, which would result in a point at the top left corner of the ROC curve, similar to the ROC plots of Fig. 12. It confirms the promising performance for the proposed methodology that depends on the efficient feature representation capability of convolutional auto-encoder. Tables [2-5] lists scores of each of these important performance metrics recorded during k-fold model evaluation for Model-A and Dual CNN for different batch configurations. The thorough analysis of outputs obtained by both these models for each fold, clearly highlight the better performance delivery by Dual CNN. This stacked CNN maintains its efficiency for the considered classification task for all batch sizes.

Table 2. Classification report of Model A and Dual-CNN for batch size 32

Fold	Model A					Dual-CNN				
	Precision	Recall	F1-score	Accuracy	AUC	Precision	Recall	F1-score	Accuracy	AUC
1	0.90	0.85	0.86	0.87	0.96	0.99	0.99	0.99	0.99	0.99
2	0.94	0.94	0.94	0.94	0.96	0.97	0.96	0.96	0.97	0.97
3	0.83	0.72	0.72	0.75	0.95	0.99	0.98	0.98	0.98	0.99
4	0.99	0.99	0.99	0.99	0.98	0.96	0.96	0.96	0.99	0.98
5	0.89	0.82	0.83	0.84	0.99	0.92	0.94	0.91	0.98	0.98

Table 3. Classification report of Model A and Dual-CNN for batch size 64

Fold	Model A					Dual-CNN				
	Precision	Recall	F1-score	Accuracy	AUC	Precision	Recall	F1-score	Accuracy	AUC
1	0.90	0.85	0.86	0.87	0.96	0.92	0.91	0.91	0.92	0.97
2	0.94	0.94	0.94	0.94	0.96	0.98	0.99	0.98	0.98	1
3	0.28	0.50	0.36	0.56	0.82	0.94	0.93	0.93	0.94	0.97
4	0.84	0.69	0.68	0.73	0.97	0.89	0.86	0.87	0.87	0.98
5	0.78	0.51	0.37	0.57	0.94	0.87	0.86	0.87	0.87	0.95

Table 4. Classification report of Model A and Dual-CNN for batch size 128

Fold	Model A					Dual-CNN				
	Precision	Recall	F1-score	Accuracy	AUC	Precision	Recall	F1-score	Accuracy	AUC
1	0.95	0.93	0.94	0.94	0.99	0.98	0.97	0.98	0.98	0.95
2	0.28	0.50	0.36	0.56	0.92	0.96	0.96	0.96	0.96	0.97
3	0.82	0.65	0.62	0.69	0.98	0.88	0.86	0.87	0.87	0.98
4	0.79	0.58	0.52	0.63	0.94	0.94	0.93	0.94	0.94	0.97
5	0.97	0.97	0.97	0.97	0.99	0.79	0.79	0.79	0.79	0.97

Table 5. Classification report of Model A and Dual-CNN for batch size 256

Fold	Model A					Dual-CNN				
	Precision	Recall	F1-score	Accuracy	AUC	Precision	Recall	F1-score	Accuracy	AUC
1	0.83	0.70	0.69	0.74	0.93	0.98	0.97	0.98	0.98	0.95
2	0.92	0.88	0.89	0.89	0.98	0.96	0.96	0.96	0.96	0.97
3	0.81	0.61	0.56	0.66	0.98	0.88	0.86	0.87	0.87	0.98
4	0.28	0.50	0.36	0.56	0.99	0.94	0.93	0.94	0.94	0.97
5	0.83	0.67	0.65	0.71	0.99	0.79	0.79	0.79	0.79	0.97

The result of the presented methodology is improved in comparison to the existing methodologies even with less complex deep neural structure. It uses simplified CNN as opposed to the graph convolutional neural network (GCNN) and exhibits best performance with batch length 32. Let's say P is a set, comprising of all assessment metrics, *s.t.* $\mathrm{P} = \{\mathrm{Precision},\ \mathrm{Recall},\ \mathrm{F1-Score},\ \mathrm{Accuracy},\ \mathrm{AUC}\}$. Scores listed for each evaluation metrics $\mathrm{m_i} \in \mathrm{P}$ of the proposed idea are computed using Eq. (8). Here, j represents each fold of the total k folds, which is *5* in this case. For better insights of the comparative improvement, Table 6 lists the scores of relevant evaluation parameter.

$$\forall m_i \in P, m_i = \sum_{j=1}^{j=k} S_{i_j} \ / \ k \tag{8}$$

Table 6. Comparative analysis with state-of-the-art work.

Authors	Year	Prediction technique	EEG length (s)	Results (in %)
Wagh et al. [19]	2020	GCNN	10	Accuracy: 85, Sensitivity: 74, Precision: 99, F1-score: 84, AUC: 90
Usman et al [11]	2021	CNN	29	Accuracy: 89.98, Sensitivity: 93, Specificity: 92.5
Singh et al.[12]	2022	LSTM	30	Accuracy: 98.14, Sensitivity: 98.51, Specificity: 97.78, F1-score: 98.23
Presented methodology-I	-	Vanilla CNN	25	Accuracy: 87, Sensitivity: 86, Precision: 91, F1-score: 86, AUC: 96
Presented methodology-II	-	Dual CNN	25	Accuracy: 98.2, Sensitivity: 96.7, Precision: 97, F1-score: 96, AUC: 98

6. Conclusions and Future Scope

The presented work suggests an efficient identification methodology for early diagnosis of epilepsy with the help of EEG recordings and deep learning architecture. The suggested methodology demonstrates the effectiveness of feature embedding of EEG with a CNN network, for EEG-based epilepsy detection. After extracting these meaningful features from EEG signals, they are classified using another CNN architecture that results in high accuracy in classifying epilepsy and non-epilepsy signals. The proposed approach has several advantages over existing methods, including the ability to handle complex temporal patterns in EEG signals and the ability to reduce the impact of noise and artifacts.

The promising performance of this study suggest that feature embedding using CNNs could be a valuable tool for EEG-based epilepsy detection and pave the way for future research in this area. However, further investigation is needed to validate these findings in larger datasets and in clinical settings. Moving forward, there is a possibility of utilizing additional deep learning techniques to improve the feature representation of EEG recordings for better prediction accuracy of epilepsy. These techniques may include various forms of recurrent neural networks (RNN), Transformers, reinforcement learning, and meta-learning. Furthermore, this approach can also be extended to classify other brain-related health conditions, in addition to epilepsy.

Acknowledgment

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