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**Research Article**

# Realization of EEG-based multi-label classification with Convolutional Neural Networks

**Sneha Mishra[1*], Umesh Chandra Jaiswal[2]**

[1]Department of Information Technology and Computer Application, Madan Mohan Malaviya University of Technology, Gorakhpur-273010, UP, India.
*** Corresponding Author Email:** snehamishra216@gmail.com - **ORCID:** 0009-0006-1209-4114

[2]Professor, Information Technology and Computer Application Department, Madan Mohan Malaviya University of Technology, Gorakhpur-273010, UP, India
**Email:** ucj_jaiswal@yahoo.com- **ORCID:** 0000-0002-5554-086X

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**Abstract:**

This paper presents a method for multi-label classification on source EEG signal datasets using DCNN and GPReLU with various signal patches. Performance has been appraised using ROC Curves for multi-label classification. Emotion is a phenomenal neurological expression that releases bio-signals with electrical voltage in the brain, which is read through as EEG signals. Reading the EEG signals and analyzing them is carried out for many purposes in science and technology. A common DCNN can simply classify the signal datasets, which often is inaccurate, although classified signal entities may contain features of other classes. Classification in uncertain data leads to class imbalances. Therefore, multi-label classification suffices the need for data analysis which anatomizes the EEG signal data as containing features of many categories. A DCNN with Geometric Parameterized ReLU is introduced to smoothen the pooling activity and work swiftly on various image patches of the source EEG signal image datasets.

## 1. Introduction

Seizures are thought of as mythological and ephemeral prevalence, but in contrast they are the physical acts of brain electrical stations. These brain functions work on overpowering or under-powering situations and are basically a central nervous system disorder that affects all ages and genders. This may also be possibly due to the past experiences and subconscious reactions of brain. The emanation of chemical charges as chemical blips of isolation is called neuronal discharge. This occurs during the interaction of neurons for the success or failure in the formation of thoughts, which unpredictably without any warning leads to loss of attention on the body′s physical presence. Seizures can cause loss of consciousness and involuntary movement of limbs, oscillations in breathing, constant staring, and a stoned feeling in the body. Seizures are caused by miscommunications between the brain and the internal and external peripheral constituent parts of the body. Electroencephalography, a neurophysiologic activity, measures the electrical signals from bunches of neurons in the brain through electrodes, resulting in an electroencephalogram (EEG). A clinically manifested seizure shall only be analyzed with readings from the scalp using an EEG. The EEG is a multichannel and noninvasive method for reading the electrical status of the brain; however, various characteristics are influenced, differing from each patient [1-4]. The nature of the data produced by EEG is multivariate time series from multiple channels embedded with dynamic correlations. Therefore, declaring a patient's seizure onset becomes difficult as sometimes the characteristics influenced show considerable variability in EEG. Even seizures onset on one patient might resemble as benign with another. During analyses, when detection is confined to classifiers with a particular set of seizures, an impressive performance might come into notifications by the classifiers. Spatial analysis methods explore EEG records collected from various positions on the head, having an electrode placed on spatial positions. The design of spatial analysis methods consists of the operations at cortical sources projecting to electrodes of select montages containing various spatial locations. The multi-label classification has great operational significance as most applications use it **[5]**. In general, where there is a continuous increase of data, to meet the urge of predicting multiple labels, the multi-label classification suffices.

## 2. Overview

The text categorization in information retrieval systems widely uses multi-label classification, where each classified entity is identified simultaneously with multiple labels based on the content given in various topics. In computer vision and image processing, multi-label classification proceeds to identify label-sets for each instance of the object in the image.

Deep Learning and CNN have already achieved accolades on EEG data sets, especially CNN renders uniquely extracting all static information from timestamps [6-7]. As known from consensus object classification [25] is a high-level cognitive task, the dynamic correlations from the past and future respond with certainty and state [8]. The factors drawn from this phenomenon are helpful in building deep learning models for activity analyses of the human brain.

### 2.1 Entropy in EEG

Entropy measures the uncertainty in data, which almost represents the quantitative output of some predictable configuration. Entropy is used to measure the disorder in a system in general. The concept of entropy is applied to electroencephalography to measure the signals' uncertainty or random patterns. The signals are sampled, from each sample, the time crest is notified to make the unpredictable as predictable. If still the signals are unpredictable, certain transformations are assumed to correct the signals to make them meaningful. One way, for a larger accumulation of EEG signals, measuring entropy helps preprocess the signals and prepares them suitable for the classification process. An entropy measure is chosen to convert or transform uncertain signals into standard signals. An entropy measure makes implicit assumptions to make the signals meaningful and quantify their importance. The application of entropy measure on signals is challenging, such that the experiment is a priori; therefore, the meaning to be derived out of randomness is not known. The entropy measure is affected by the time-domain(TD) and frequency-domain(FD) of the signals based on the signal-noise ratio. Thus, it is assumed that the input for the experimentation for finding the epileptic seizures have already been treated with entropy measures and corrected with suitability meaningfully.The application of classification deserves good consistency apart from high accuracy. Due to heterogeneous characteristics and a wide range of possibilities due to new behavioral aspects, the entropy of the data needs to be studied. The characteristics of a patient with epilepsy are traced in the recordings as four periods: interictal, pre-ictal, seizure, and post-ictal. The entropy of short-term EEG is implemented to extract characteristic features from the channels of EEG and supplied as input to the DCNN models.

### 2.2 CNNs and EEG

The challenging element in the diagnosis of epilepsy is classification. Classification of epilepsy in different states is an experiment every researcher needs to explore the characteristic differences from the readings of each individual. By transforming epileptic signals into power spectrum density energy diagrams, Yunyuan et al. proposed a method for classifying epileptic signals [1]. Further, the Deep CNN is employed for classification based on the features selected from the four categorical epileptic states interictal, pre-ictal, seizure, and post-ictal. On the basis of epileptic EEG data collected by the CHB-MIT laboratory, the experiments were validated by case studies. The accuracy of classification achieved can reduce the likelihood of frontal seizures occurring. DCNN algorithms based on LSTMs are much more efficient than DCNN algorithms based on LSTMs. J.X.Chen et al. has proposed a CNN model for classifying epileptic disorder data, which employs end-to-end learning of signals and states of epilepsy with spatial and temporal dimensions [2]. A Bayesian model is proposed in the framework, which does emotional binary classification. Almost the shallow machine learning models like bagging tree, support vector machine, linear discriminant analysis admixed with Bayesian learning model are employed. A verified DEAP dataset with 32 subjects is used in the framework. The CNN models are proven suitable for learning and classification and stably identify epileptic states. In a new study, Rahib Abiyev et al. propose yet another CNN model for epileptic EEG data classification, in order to classify epilepsy, it must be a chronic neurological disorder that produces different types of EEG data and requires a combination of methods in CNN [3]. Tengfei Song et al. has proposed that DGCNN, deep graph convolutional neural networks have a profound influence in the classification models of CNN, so far employed [4]. The nature of dynamic learning has explored many intrinsic relationships among the features extracted from the typical EEG data sets. DREAMER data sets are used in the experimentation, where better features recognition is extracted with both dependent as well as independent to be subjected. An EEG data set was montaged at different points in Cheng Lian Liu et al.'s study of multi-view convolutional neural networks. The unpredictability of the seizure challenges is met by extracting features from frequency and time domain aspects **[5-6].** Even an introductory study of electroencephalogram needs attention to understand the features and the epileptic states temporally connected to several montage points, which is prudent with applications of CNN architectures. The process of selecting features and subsets of features from the large collection of features, to achieve the accuracy of modeling and finding the best fit for the learning model, to obtain the clear and actionable insights of the model, constitutes devising an algorithm for feature selection. Most classical methods for feature selection are variants of simulated annealing and genetic algorithms, whereas in evolutionary algorithms, stochastic approaches play a lead role in some areas. A minimal set of features are used to detect the categorical epileptic states to identify the severity of epilepsy. Initially, the features are manually selected from the dataset, and then the algorithmic approach is used to extract the features and compare them with the manually selected ones, such that the procedure employed to extract features is appropriately asserted. The benchmark dataset is traversed to find out the data which contain the features as can be extracted by the algorithm. The seizure is categorized as simple partial seizure (SP), complex partial seizure (CP), focal non-specific seizure (FN), generalized non-specific seizure (GN), absence seizure (AB), tonic seizure (TN), tonic-clonic seizure (TC), and myoclonic seizures. Myoclonic seizures rarely occur and are very mild to identify, so they are exempted from the study **[9-10]**. Using clinical manifestations, the source data of EEG recordings were annotated and made available for the experiment.

## A. Feature Extraction

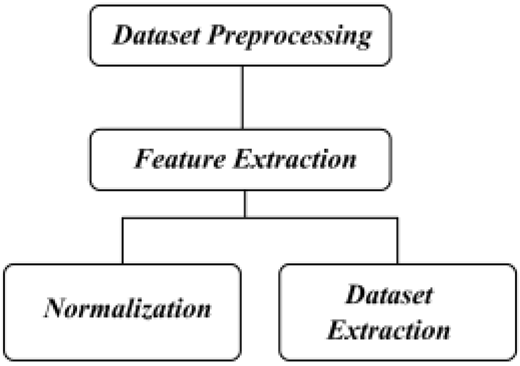



***Figure 1.*** *Overview of Feature Extraction*

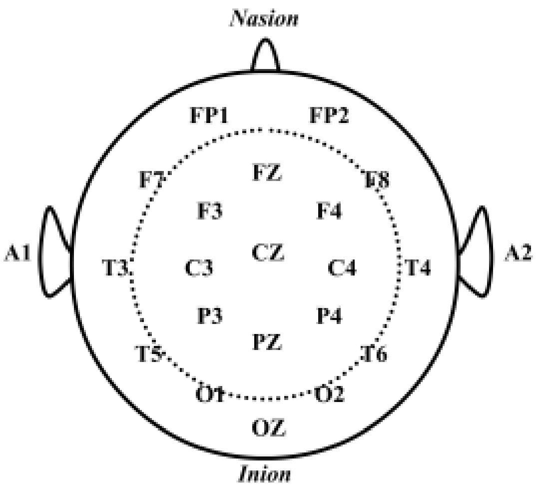



***Figure 2.*** *International System of Electrode Placement – Unipolar Channels.*

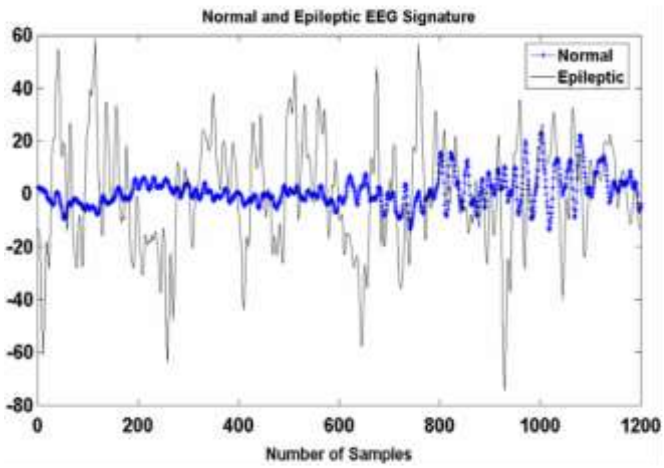



***Figure 3.*** *Wave Signature of Normal and Epileptic EEG.*

### B. Class Imbalance

The concept of class imbalance is related to imbalances in classification. The predictive modeling of classification faces an insufficient training dataset where the knowledge required for complete classification is missing. To overcome this imbalanced classification problem in deep learning with images, certain precautions must be considered. The first of the activities is identifying the frequencies of categories of images in the collection, where the training data set shall have a proportionate distribution of the categorized data sets. Proportional distribution is not as same as equal distribution but based on the frequencies of the categories of the images. For representing the training data sets in typical experimentation of image classification, the training data sets shall be composed for less frequent categories of images and more frequent categories of images as to how their frequencies appear in the original datasets [11].

The contribution in the paper is, the waves of the different common signatures are found in most images, carefully picked to build the training dataset. The following algorithm proposes the ideal fit in selecting the training dataset. The second activity to overcome the imbalance in classification is to merge the near-identical classes. All similar-looking objects are combined into a single class, thus preventing the formation of many classes [12-13]. In some typical classification applications, resampling is done for the classes to avoid the misclassification of objects.

### C. Data Model and Uncertainty

The EEG recordings data sets are considered for evaluation of the model and understand the uncertainty. The data is temporally influenced by parameter ***t***. a mathematical model representing the prediction of the cumulative number with the evolution of time for ***N*** observations i.e., ***N***(***t***), are seizures, Let ***S*** denote the effect of seizure, which can be denoted by

$$S = \frac{dN/dt}{N} \rightarrow (1)$$

***S*** is a temporal and linear-dependent function of ***N***. Let the constant $N_j$ denote the a cumulative number of cases with the similar seizures of electronic recordings. Considering that ***S*** is negligible then $N = N_j$, then

$$S = \alpha(t)\left(1 - \frac{N}{N_j}\right) \rightarrow (2)$$

By substituting (2) in (1) we get

$$\frac{dN(t)}{dt} = \alpha(t)\left(N(t) - \frac{N(t)^2}{N_j}\right) \rightarrow (3)$$

This is called as Ricatti equation, which is specified by time independent function and a constant parameter $\alpha(t)$ and $N_j$ respectively. This equation has played significant role in many health care applications, especially in chronic case studies [11], [14-16]. This equation is widely used in mathematical biology, particularly when the problems akin to multi-label classifications and uncertainty rise. This rise gives to equation (1), where $\alpha$ is substituted by 1 and ***t*** by $\tau$. Thus the equation can be linearized by the change of variables as

$$N = \frac{dy/d\tau}{y} \rightarrow (4)$$

And further by substituting the (4) in (1), we get

$$\frac{d^2y}{d^2\tau} = \frac{dy}{d\tau} \rightarrow (5)$$

Where on solving the validity of the model increases as the ***t*** increases. The very important parameter in the above equation is time, as changes in EEG electronic recordings are uncertain temporally. The seizure is ascertained for the times of the parameter as derived from the equation (5).

### D. EEG Signals to EEG Images

There are five interesting sub-bands of frequencies for EEG, viz., alpha, beta, theta, delta, and gamma, which usually span the 0 Hz to 64 Hz range; almost all the frequencies are prone to noise. The frequency of all possible power shots of EEG is 1763.61 Hz, which is considered sampling frequency. Conditionally the maximum frequency for extracting EEG with least noise is 86.81 Hz, or evenly half in the sampling frequency is considered. Some wavelet transformation does not allow the extraction of specific signals, 0 Hz to 64 Hz range is considered ideal frequency. The selection of appropriate segments of the wavelet representing the frequencies and converting them into images by decomposing frequencies to build the image data required for the analyses. An example is delegated with all five possible frequencies of an interictal EEG signal [12-14]. The generic Structure of a converted EEG data file consists of the readings collected at each pass of scanning at specific frequencies of a subject.Numbers of trials are executed on various sensor positions of unipolar setup, with a considerable number of samples pertaining to each subject. As shown above, time, matching conditions, and channels are observed and recorded. The sensor values readings are recorded for the subjects with different positions are between -48.33 and 31.057. Whereat FP1: between -6.48 and 23.794, at FP2: between -7.406 and 20.915, at FC1: between -4.405 and 8.779 at FC2: between -2.625 and 7.629 at FC3: between -5.493 and 9.644 at FC4: between -6.002 and 8.158 at FC5: between -16.541 and 17.151 at FC6: between -8.667 and 9.888.

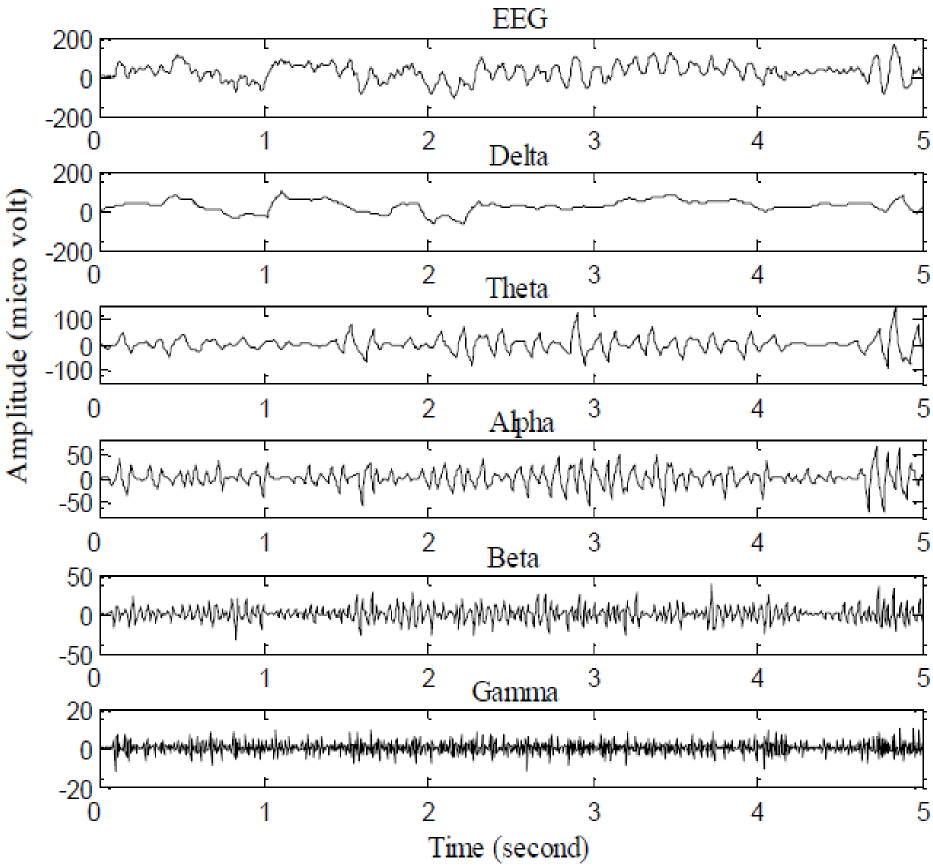
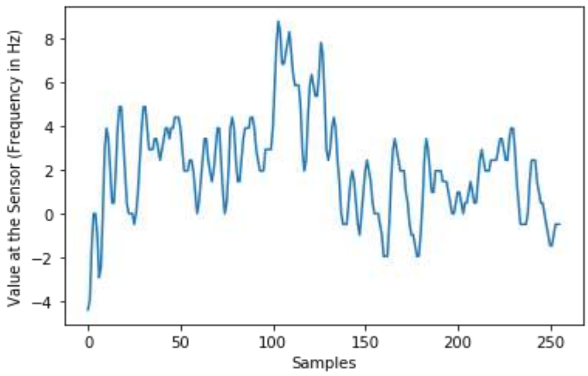



***Figure 4.*** *Image of EEG Interictal signals after decomposition of band-limited into five sub-bands*

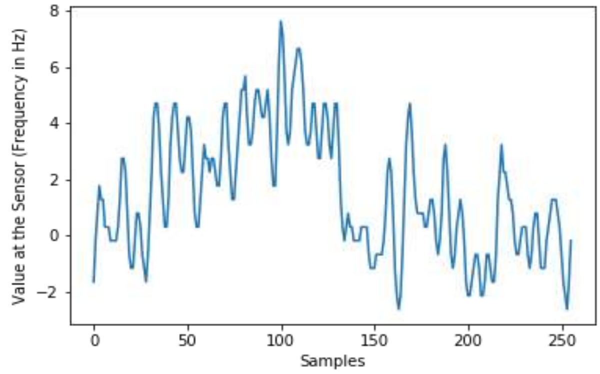
| | Unnamed: 0 | trial number | sensor position | sample num | sensor value | subject identifier | matching condition | channel | name | time |
|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 7 | 30 | FP1 | 2 | -5.503 | a | S1 obj | 0 | co2a0000364 | 0.007812 |
| 3 | 8 | 30 | FP1 | 3 | -3.550 | a | S1 obj | 0 | co2a0000364 | 0.011719 |
| 4 | 9 | 30 | FP1 | 4 | -0.621 | a | S1 obj | 0 | co2a0000364 | 0.015625 |
| 5 | 10 | 30 | FP1 | 5 | 1.821 | a | S1 obj | 0 | co2a0000364 | 0.019531 |
| 6 | 11 | 30 | FP1 | 6 | 2.309 | a | S1 obj | 0 | co2a0000364 | 0.023438 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 16378 | 16446 | 30 | Y | 250 | -2.411 | a | S1 obj | 63 | co2a0000364 | 0.976562 |
| 16379 | 16447 | 30 | Y | 251 | 1.007 | a | S1 obj | 63 | co2a0000364 | 0.980469 |
| 16380 | 16448 | 30 | Y | 252 | 3.937 | a | S1 obj | 63 | co2a0000364 | 0.984375 |
| 16381 | 16449 | 30 | Y | 253 | 3.937 | a | S1 obj | 63 | co2a0000364 | 0.988281 |
| 16382 | 16450 | 30 | Y | 254 | 2.472 | a | S1 obj | 63 | co2a0000364 | 0.992188 |

16381 rows × 10 columns

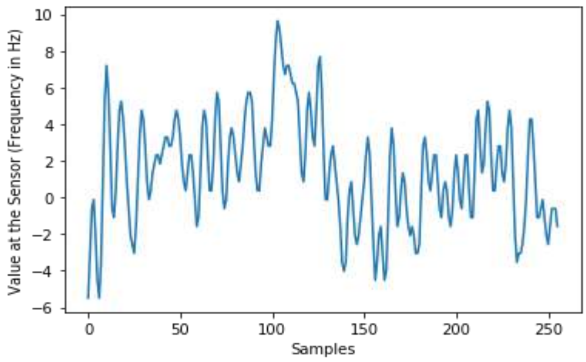
***Figure 5.*** *Generic structure of the EEG Interictal signals*



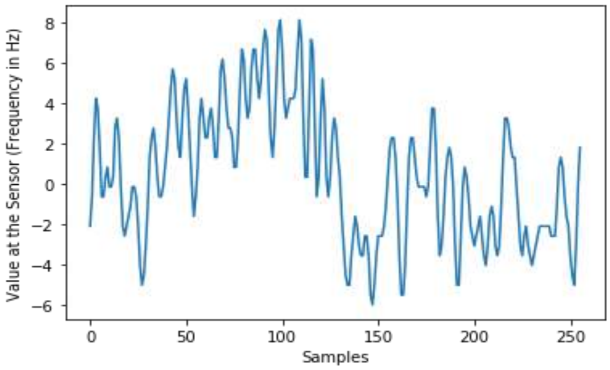

**FP1: between -6.48 and 23.794**



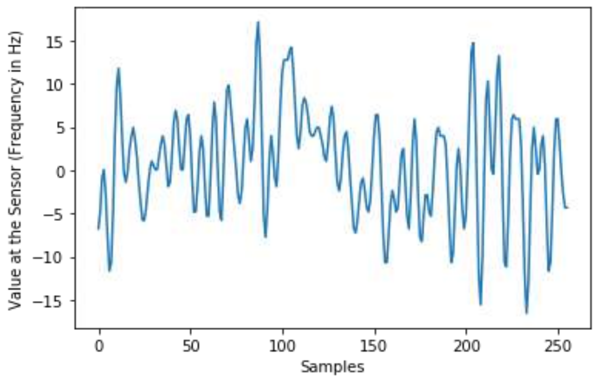

**FP2: between -7.406 and 20.9**



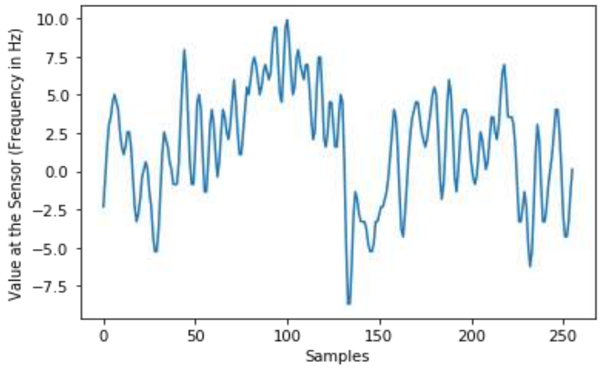

**FC1: between -4.405 and 8.779**



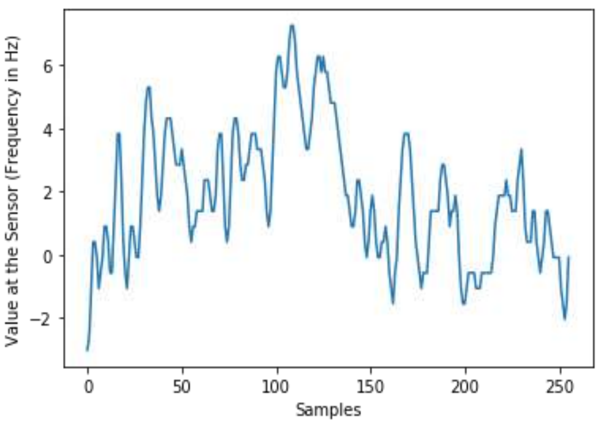

**FC2: between 2.625 and 7.629**



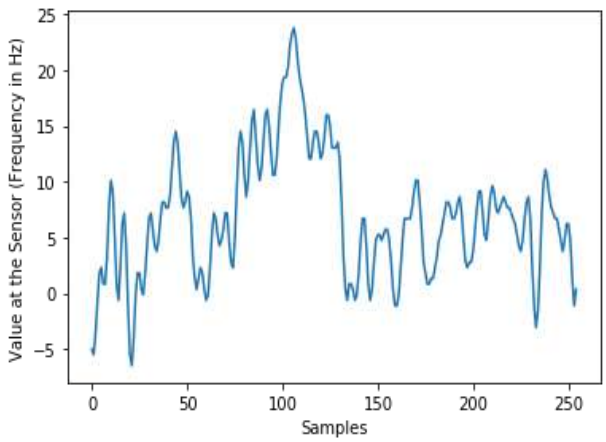

**FC3: between -5.493 and 9.644**




**FC4: between -6.002 and 8.158**




**FC5: between -16.541 and 17.151**




**FC6: between -8.667 and 9.888**

***Figure 6.*** *The sensor value readings on selected subjects at positions of FP1, FP2, FC1, FC2, FC3, FC4, FC5, FC6.*

## 3. Literature Review

Deep learning models such as support vector machines with linear discriminant analysis, Bayesian linear discriminant analysis, etc., are often combined with CNNs. Learning EEG data is challenging, such as end-to-end automatic emotional learning, with improvisations in accuracy. Articles and publications related to several studies on ʹ*epileptic electroencephalography* are collected online from several renowned organizations, such as, IEEE, Wiley, Elsevier and so on, which is revealing the current status of technological development. In the preliminary studies, keyword-based search with automated epileptic seizure detection, EEG data, selection of EEG channels, feature selection in EEG data, conversion of EEG signal to EEG image, convolutional neural networks for EEG image data classification, and feature extraction in EEG data were investigated. In the second level of search, keywords related to automated epileptic seizure detection, analysis of EEG image data for epileptic seizure detection, entropy of EEG data, and non-linear features of EEG data were used to find research publications. Mendeley and Science Direct were employed to focus and filter on more relevant journals. Researchers have recently recommended umpteen solutions regarding the automatic detection of seizures [23-26]. Of all the analog methods followed, the time-frequency domain methods predominate in experimenting. Non-linear methods, such as machine learning methods, have achieved good performances. As opposed to signal processing methods, researchers prefer machine learning and deep learning methods to extract seizures from EEG data quickly. In [9], the author has discussed the application of machine learning in seizure detection using the CHB-MIT scalp EEG database and has yielded sublime performance factors. In [10], Qin et al. has worked on the framework development using bi-clustering and extreme learning (ELM) methods to classify seizure and non-seizure EEG data. Even though analog techniques are not completely ignored, they are used to present a new perspective on time-frequency in the classification of EEE features using local mean decomposition and support vector machines [11]. The recordings of EEG are decomposed, and empirical analysis is undertaken, using wavelet transform with least squares – support vector machine in the classification of focal and non-focal classes. Singular value decomposition and random forests are used in absolute epileptic seizure detection [12-17].The manuscript is organized as follows: The EEG data is collected and preprocessed by the entropy estimation method. Conversion of EEG data into EEG images. Feature selection and extraction with computational complexities are discussed. Categorization of epileptic and non-epileptic EEG data. Application Multi-label classification to identify the degree or type of seizures from the EEG data.EEG signals are mixtures of noise and other artifacts; most of the signals are raw, often used to detect emotions and classify EEG signals for the same. Some critics and researchers promoted channels and frequency bands related to recognizing emotions by decoding analog EEG signals traced with multiple frequency meters. Motor imagery skills are not the least for the CNN specialists to identify the involuntary actions of hands of the right and left [24]. Deep belief networks made first and fast classification and detection with purposeful probable anomaly measurements. Other CNNs and EEG specialists detected the sleep stage of a human from the EEG signals for attentiveness and cognitive features of the vehicle drivers. The influence of noise has raised many studies to use raw EEG data in deep convolutional neural networks, where more particular research was instituted for Alzheimerʹs disease. Conversion of raw data into bands of frequencies and noise filtering for classification were attractive preprocessing and methodological achievements.As opined in the article [13-15], the classification of images with deep convolutional neural networks is accomplished with eight learned layers, five convolutional and three fully connected layers. The standard model of neuron to get the output $f$ is defined as $f(x) = \tanh x$ or as equivalent to $f(x)=(1+e^{-x})^{-1}$. In terms of the factors of time for training, the saturating nonlinearities are very slower than non-linearity that are non-saturating. The type of neurons with non-linearity are referred to as ReLU. In each convolutional layer, only kernels from the previous layer are connected to kernel maps; however, neurons are connected to all neurons from the previous layer.The article [16-22] proposes that the features of the EEG signals are fed into different classifiers, and their performances are empirically compared regarding the frequencies emitted and the structures in the readings. The proposed methodology's efficacy is studied with a single-channel EEG signals database, and the number of epochs is recorded. The different sets of classes are used to formulate a multi-class classification problem, where the performance of the methodology is evaluated for each multi-class in the classification problem. The basic characteristic of single-channel EEG signals is nonlinear and non-stationary; the non-stationary signal decomposition methods such as iterative filtering is used in decomposition.

***Table 1.*** *Applications of DCNN on EEG Signal Image datasets in varied applications [2],[8],[18-19],[21-24],[26 ].*

| S.No. | Authors | CNN and Methods | Epileptical Status | Accuracy |
|---|---|---|---|---|
| 1 | Rajendra Acharya et. al. | 13 Layer DCNN | Normal, Preictal and Seizure classes | 88.67% |
| 2 | Yimin Hou et. al. | Weight Minimum Norm Estimation, CNN for Motor Imagery | summarized to be as Ictal, Preictal | 93.30% |
| 3 | W-L Mao et. al. | CNN with Complete Wavelet Transform Methods | normal epileptic seizures | 72.49% |
| 4 | Ciaran Cooney et. al. | CNN in BCI, Transfer Learning | Tuning BCI using TL | 35.68% |
| 5 | Lan Ma et. al. | CNN based joint-biometric system | EEG-based 10-class classification | 88.00% |

Encephalogram is a device to aid the study of epilepsy [17]. Nearly 50 million people have epilepsy around the world. Automated classification of EEG signals with a deep CNN model is the article′s central idea, where the signals collected are classified as normal, preictal, and seizure classes. Convergence and accuracy are promised in [17], though the model in the article is not as best, it can be improved to achieve more than 88.67% even. According to Yimin Hou et. al., decoding EEG signals to identify the four-class motor imagery is accomplished using weighted minimum norm estimation. The study uses a particular class of case studies and tests them against the Physionet database of brain-electric signals. An approach to developing global classification, is seen for the motor imagery using deep convolutional neural networks. The mean accuracy for the overall experiment is observed to be 93.30%; however, the best class of case studies of physio-scouts can be considered to achieve further improvisation of the methods. A simple CNN architecture has been proposed by W-L Mao et al. for the classification of EEG data, where the core of the diagnosis involves identifying and analyzing the electro-encephalography [18-19].The classic examples of GoogleNet and AlexNet were used to demonstrate the operational significance of CNNs in EEG data analysis. Ciaran Cooney et al. has worked on Brain-Computer Interfaces, Transfer Learning was employed in BCI to achieve the classification of EEG data [20], [26]. Other TL methods are compared and found that the TL for BCI in their work has better performance. It has been recorded with an accuracy of 35.68%, though not an average scale in the performance. It challenges the competing methods of TL for BCI. In [21], the method of finding the state of mind during rest and the normal electrical signals as the biometric have been proposed, which was also referred to as brainwave patterns. REC and REO (Resting State with Closed Eyes and Open Eyes) are two states in which EEG data can be collected from the subject, thus collected data is used in CNN systems to define the biometric signature of the subject, which has achieved 88.00% accuracy in biometric identification for a minimum of 10-class classification [22]. Therefore, the Deep Convolutional Neural Networks has a profound confluence with the methods of EEG data analysis and diagnosis in epilepsy disorders and seizures and for a varied collection of applications.

## 4. Multi-Label Classification

One of the essential categories and frequently used in multi-label classification is the transformation method. A multi-label classification problem employs an approach to convert either into a single-label classification or regression.

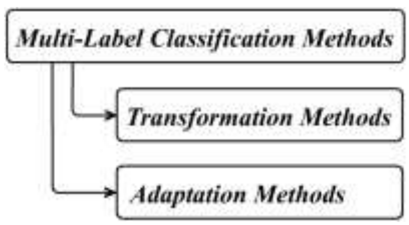



***Figure 7.*** *Types of Multi-Label Classification methods.*

A huge bibliography of algorithms contributes to this nature of multi-label classification turning into a single-label classification; however, it is inevitable to resist the classification problem. Therefore, an adaptation method is chosen for many applications to handle the data with multi-label characteristics. As for a fundamental learning problem, C4.5 is employed to overcome the transformation problem and convert it into an adaptation problem. The frequency of the class is based on the data frequencies available in the whole data set. Based on the frequency of the class the merge process of the class into another is based on the entities and the entropies of the class, which also yields to the predictive method of adapting into multi-label classification. At the core, the problem transformation is employed, and then to overcome the ambiguity of sharing the class labels, an adaptation mechanism is introduced based on the frequencies and entropies. In this situation, the question to ponder is 'not all the elements of data sets are equivalent to the multi-label. A set of labels $|L|$ is noted to compare all the other classes whether or not they belong to the set, but for some applications number of labels that have to be compared is too large, and for some, it is tiny. The two factors called label cardinality, and label density are thus introduced to address the issues. The following definitions clarify the computation of the two factors.

$$Label\,Cardinality\,(D) = \frac{1}{|D|}\sum_{i=1}^{|D|}|Y_i| \rightarrow (1)$$

Where the cardinality ***D*** is represented as the average number of labels for the examples of ***D***.

$$Label\,Cardinality\,(D) = \frac{1}{|D|}\sum_{i=1}^{|D|}\frac{|Y_i|}{|L|} \rightarrow (2)$$

Where the cardinality ***D*** is represented as the average number of labels for the examples of ***D*** with respect to ***L***.In the present work, the features of each label are ascertained for the merging of the classes and comparing with the said ***L***. The features of the EEG signal data are observed in different texture forms and represented as a template to refer to the similarity among the classes. Therefore, first, the identification and declaration of class labeling are introduced in the simple CNN based on the similarity features of the EEG signals data pertaining to different instances of different subjects [23-26].EEG signal images of particular montage points of all interictal, pre-ictal, seizure, and post-ictal states are generated using pyplot of matplotlib. To accommodate the 250 samples with voltage variations, the EEG signal image of 380x260 pixels is generated. The gross generation and the collection of the EEG signal image datasets reflect all the properties of *interictal*, *pre-ictal*, *seizure,* and *post-ictal* but not of all in full. Therefore, the datasets need multi-label classification. The collected EEG signal image datasets do not classify the labels, but at the training stage, they are categorized; instead, they represent the features of all the periods; however, they are classified using single-label classification, as they belong to the individual bins representing a label. The properties of the four periods viz., *interictal, pre-ictal*, *seizure,* and *post-ictal* are highlighted and traced as a guide for the training data, such that the training on the EEG signal image datasets can define the multiple labels for each data entity. The indexed data for the EEG signal image datasets are built to note the categories of periods. Further for, each entity image of the datasets is qualified with the percentage of period category, indicating that an entity belongs to multiple classes and therefore labeled, thus providing the pathologists to assess the severity of the epileptic effect.

**Network Setup**

The convolutional layers of the network consisting of ReLU and parametric ReLU (*p*ReLU) are the vital components of the sequential model of the proposed CNN. The parameter for the parametric ReLU (*p*ReLU) is derived from the computation of the Geometric Mean of two positive values.

**Parametric ReLU (*p*ReLU):**

In many applications, CNN models stand pervasive, particularly in image processing. Classification of Images, Object Recognition, and Object Detection support various strategies of learning which are phenomenally accepted universally in all Image Processing and Computer Vision applications. The purpose of the Geometric Mean is to introduce the parameter of the Parametric ReLU, which might hold a specific reason. Since the DCNNs explore learning behavior exponentially, a standard is needed to select a value for the parameter found apt.An activation function determines the next level of learning during the DCNN process of input flow from layer to layer. An equation that can mitigate with the negative values such as y = max(0,x) is generally introduced in ReLU, whereas with parameter ʹa as y = a.max(0,x), attributing the geometric mean to the derivation of ʹaʹ. This aids to overcome null values as the inputs for the intermediate layers to promote the success of the learning model, which particularly raises when data is sparse. This may be compared with Leaky ReLU, where values between 0.01 and 0.001 may be assumed for the negative values, which intends to compute with small slope values, where learning will not stop, but this is suitable for dense data. In experiments with the uncertainty of data, we cannot always assure data is dense, so the choice of Parametric ReLU with Geometric Mean is once again an apt choice. Using the Geometric Mean, the care can be taken so that during the computation of the parameter, the value cannot become zero or null to make the model profitable [1]. Features of EEG signal data are observed, converting them into temporal images for a number instance on each subject, and are used as input into the CNN architecture. Characteristics and drawings about the epileptic state are demonstrated based on the features present in the input data, whether or not the subject manifests with the adverse characteristics of mental health. CNN architecture is further employed to classify the EEG image data for the categorical identification of *interictal*, *pre-ictal*, *seizure*, and *post-ictal*.The working of the proposed DCNN has elementary four convolution layers with eight feature maps. In each layer, a usual kernel size of 3 × 3 pixels is set up with ReLU to prevent intermediate saturations. Generally, a series of sampled and tested positive integers are determined for the coefficients of the parameter and tested in the ReLU, where all the values converge in pooling. Instead of a series of values, a geometric mean of the select values is considered a parameter for the variable in the ReLU function to improve efficiency [5-7]. As the initial step of the operations of DCNN, the size of feature maps is reduced even to 2 × 2 using Max-Pooling, further appended with normalization layers to enable quicker convergence after each max-pooling layer. The max-pool layer generates eight features, which are further input to the fully-connected layer. The fully connected layer consists of 256 neurons.

***Table 2:*** *Validation Parameters [5-7]*

| Parameter | Computation |
|---|---|
| Accuracy | $\frac{TP+TN}{TP+TN+FP+FN}$ |
| Error Rate | $\frac{FP+FN}{TP+TN+FP+FN}$ |
| Positive Predict Value (PPV) | $\frac{TP}{TP+FP}$ |
| Sensitivity | $\frac{TP}{TP+FN}$ |
| Specificity | $\frac{TN}{TN+FP}$ |

***Table 3:*** *Setup of Image Patches for Experiment [2], [5-6].*

| No. of Images (Patches) with Seizures | |
|---|---|
| Training | 9669 |
| Testing | 4800 |
| Validation | 4800 |
| Total Number | 19269 |

***Table 4:*** *Number of images patches per class of validation obtained*

| Positive Class | | Negative Class | |
|---|---|---|---|
| Positive Prediction | Negative Prediction | Positive Prediction | Negative Prediction |
| True Positive | False Negative | False Positive | True Negative |
| 46 | 6 | 43 | 38 |
| 52 | 7 | 37 | 33 |
| 55 | 7 | 34 | 30 |
| 62 | 8 | 27 | 24 |
| 68 | 9 | 21 | 19 |
| 74 | 9 | 15 | 14 |
| 76 | 10 | 13 | 12 |
| 80 | 10 | 9 | 8 |
| 86 | 12 | 5 | 6 |

***Table 5:*** *Validation Parameters obtained from the experiment*

| | Seizure | No-Sign |
|---|---|---|
| Accuracy | 0.967 | 0.987 |
| Sensitivity | 0.958 | 0.974 |
| Specificity | 0.948 | 0.958 |

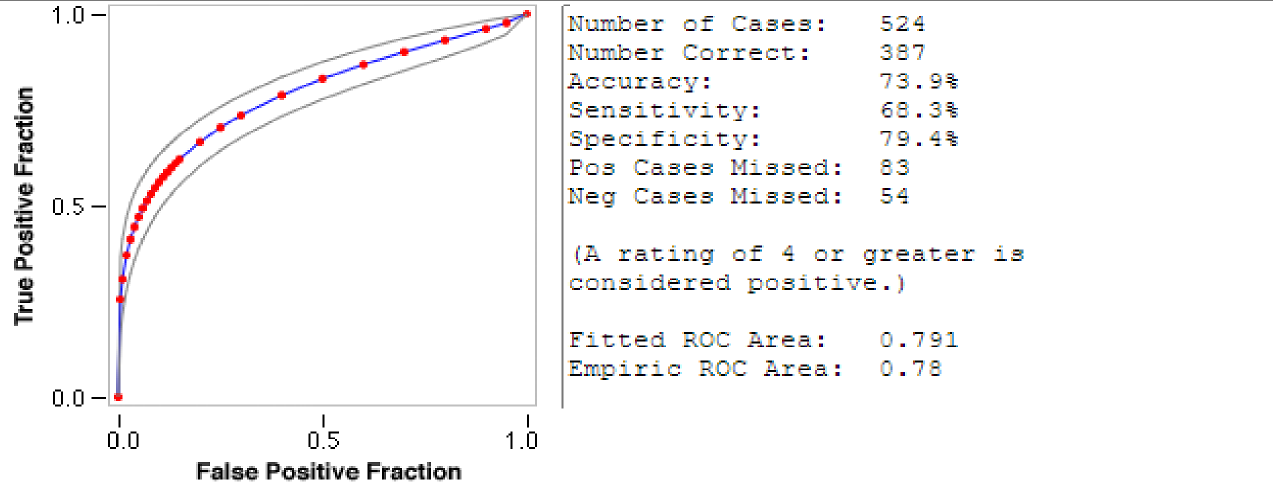
Features of the EEG image data are collected into a select category of image patches with $EEG_F$ =50, and the size of $EEG_F \times EEG_F$ segments are prepared. However, the corresponding features of the hand-extracted EEG image data of a subject at different montage points are utilized in training. During the experiment, in the augmented dataset, patches are asserted as non-overlapping, tested by flipping horizontally and vertically; about 19,269 patches result as seizures, and 36,635 were negative, which can be matched with pathological observations. The experiment is conducted by testing the model with 0 to 150 epochs. It is observed that during iterations between and around 66$^{th}$ and 70$^{th}$ epoch, accuracies are measured 96% approximately. Table 3 shows that for the training (50%), validation (25%), and testing (25%) of the total number of patches are considered [7-9].

## 5. Results and Discussions:

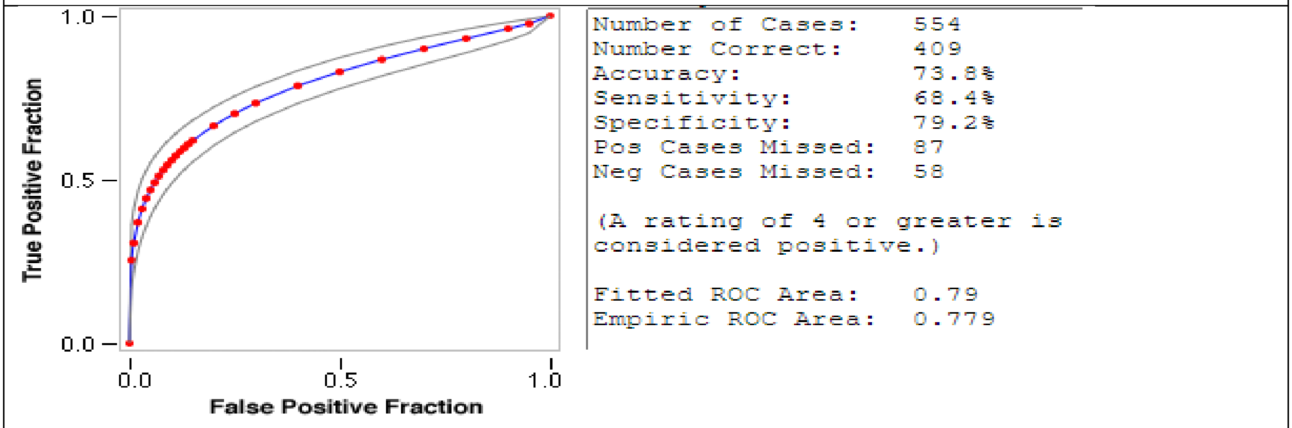
The overall experiment is executed around 150 iterations, a patch-based method is employed in the model during the experiment, and further, it is derived that pathological symptoms of seizures the accuracy, sensitivity, specificity of 0.967, 0.958, and 0.948 respectively exists and for no-sign of seizure as 0.987, 0.974 and 0.958 respectively. The number of image patches per class during validation considered to enable predictions in experimentation is shown in the following table.The collected signal recordings in CSV formats are interpreted into graphical form. The whole experiment of multi-label classification is performed on the EEG signal image datasets. From each image containing the EEG graph, patterns are identified from the images of signal patches. These patterns are periodic patterns that confine to the four stages discussed earlier; however, the overall classification is targeted to identify the combination of normal and seizure signals in the source images. Correspondence indication is maintained between the patches and the full images of EEG signal data sets [11-13], [17], [24]. The experiment is conducted with a ʹSequential model of DCNN using Keras – Tensor Flow. As the number of target labels is two, viz., ʹnormal and ʹseizure, which are detected from the signalʹs images converted from the collected data, containing the voltage frequencies of 24 montage points, the data is collected from the same subject in different temporal conditions. As the dataset is moderately large, the network is evaluated several times on the same data sets to ascertain the mean performance. A list of evaluation scores and accuracy scores is obtained. Below are the ROC curves that represent the performance of the model evaluation on different collections of image patches of EEG signal image datasets. With selected image patches and their relevance of classification into normal and seizure, the above graphs comply with the model described for the DCNN. Our model has achieved 74% of higher accuracy, which is near about the previous published paper that is 78.1% accuracy. But our approach is more sofacsticated in terms of fidelity of given achievable data. So, each of the EEG signal image entity in the dataset can be classified with two labels, ʹnormal and ʹseizure, with the relevant percentage of their existence in the source image data sets. The following table shows the percentages of labeling for the few selected signal images [2], [7].

## 6. Conclusions

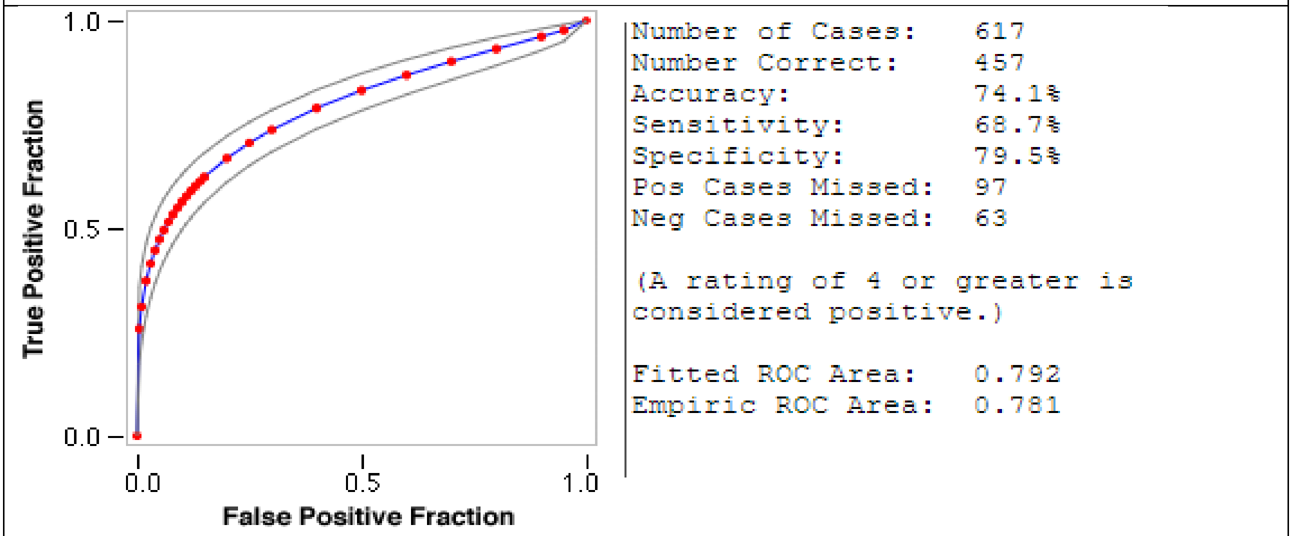
The proposed work uses EEG data from a subject with seizures and one without seizures. The collected EEG signals are converted into images using pyimage. The proposed model is tested on the dataset. Algorithmically, the signal is converted into a data set in a CSV file for each subject and for each time the signals are recorded. The proposed model for multi-label classification has shown the results with a specific percentage of labeling that each EEG signal image entity belongs to. Several experiments on EEG signal data sets have been conducted in the erstwhile research. Based on the application, they achieve different levels of


True Positive Fraction
False Positive Fraction
1.0
0.5
0.0
0.0
0.5
1.0
Number of Cases: 524
Number Correct: 387
Accuracy: 73.9%
Sensitivity: 68.3%
Specificity: 79.4%
Pos Cases Missed: 83
Neg Cases Missed: 54
(A rating of 4 or greater is considered positive.)
Fitted ROC Area: 0.791
Empiric ROC Area: 0.78

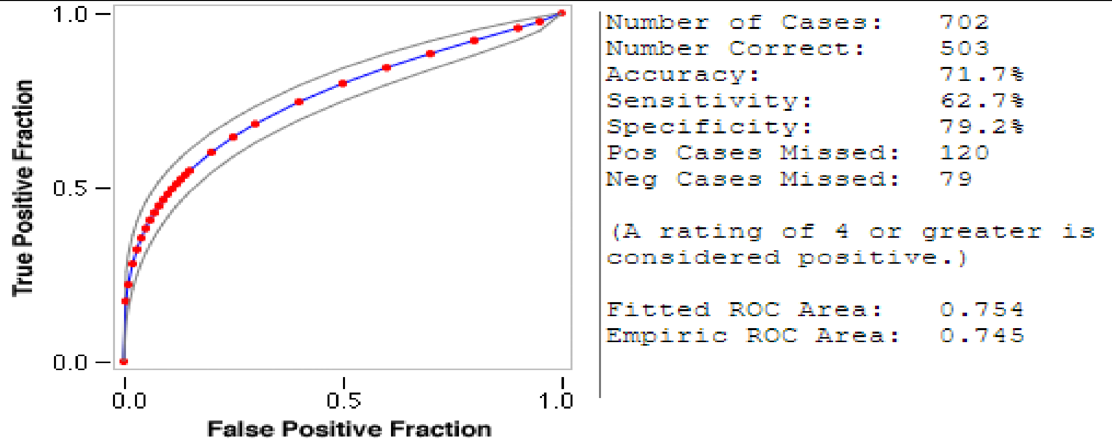
**(a)**


True Positive Fraction
False Positive Fraction
1.0
0.5
0.0
0.0
0.5
1.0
Number of Cases: 554
Number Correct: 409
Accuracy: 73.8%
Sensitivity: 68.4%
Specificity: 79.2%
Pos Cases Missed: 87
Neg Cases Missed: 58
(A rating of 4 or greater is considered positive.)
Fitted ROC Area: 0.79
Empiric ROC Area: 0.779

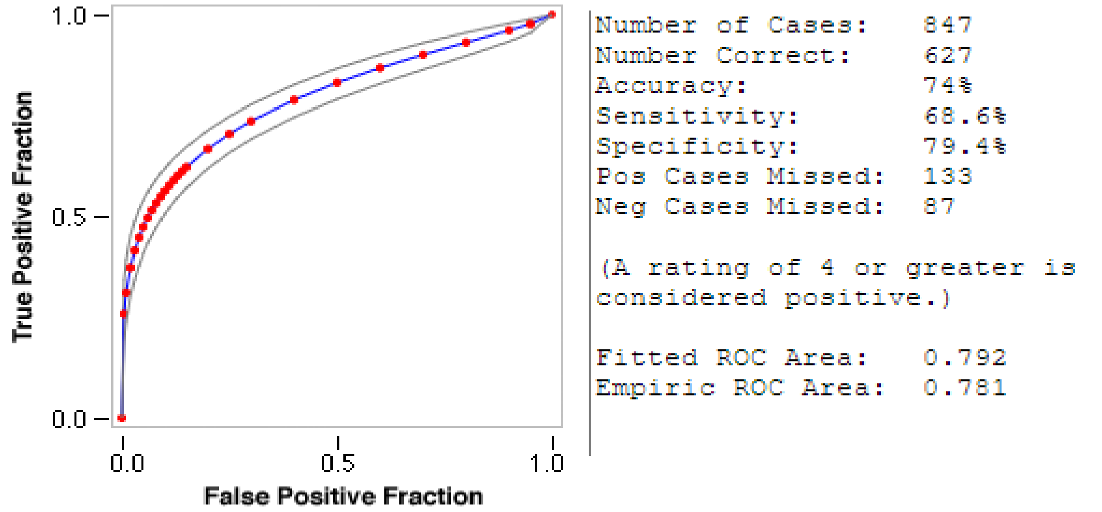
**(b)**


True Positive Fraction
False Positive Fraction
1.0
0.5
0.0
0.0
0.5
1.0
Number of Cases: 617
Number Correct: 457
Accuracy: 74.1%
Sensitivity: 68.7%
Specificity: 79.5%
Pos Cases Missed: 97
Neg Cases Missed: 63
(A rating of 4 or greater is considered positive.)
Fitted ROC Area: 0.792
Empiric ROC Area: 0.781

**(c)**

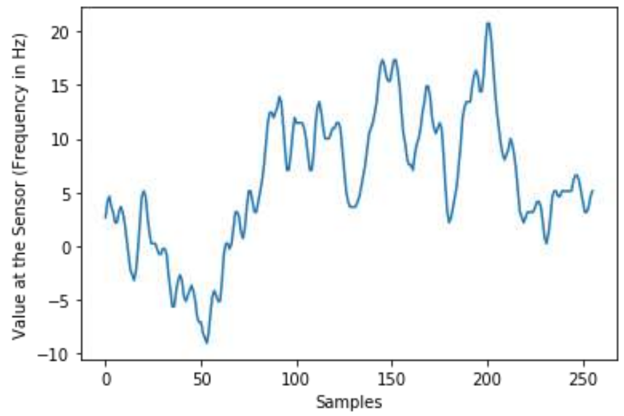



**(d)**

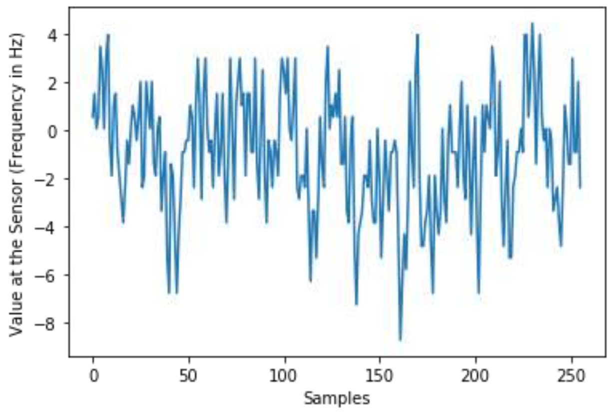



**(e)**

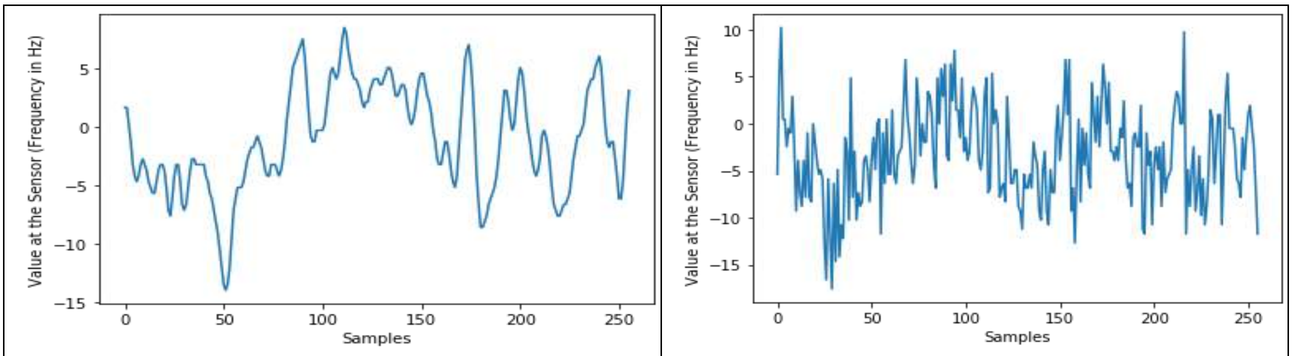
***Figure 8.*** *Repeater Operating Characteristic curve, representing the relevance of classification in the proposed DCNN*




**Normal (40%), Seizure (60%)**




**Normal (23%), Seizure (77%)**




**Normal (65%), Seizure (35%)** **Normal (33%), Seizure (67%)**

***Figure 9.*** *EEG Signal Image Entities Classified with Multiple Labels*

accuracy, and performance metrics are found to be appropriate for specific models. EEG data sets and methods are widely used in a wide variety of applications, and when combined with DCNN, the comparison of similar experiments is very rare. Therefore, the model's performance is tested with the repeater operating characteristic curves, based on the true positives and false negatives and subsequent computations of sensitivity and specificity. Practically, the complete image of the graph cannot be input into the model, so patches of the images in the EEG signal image datasets are considered for training, testing, and validations. The proposed model proved with geometric values of the parameters supplied to the ReLU, has achieved a significant level of learning to define the labels of the source image entities.

## Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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## References

[1] Gao, Yunyuan, Bo Gao, Qiang Chen, Jia Liu, and Yingchun Zhang. "*Deep convolutional neural network-based epileptic electroencephalogram (EEG) signal classification*." Frontiers in neurology 11 (2020): 375.

[2] Chen, J. X., P. W. Zhang, Z. J. Mao, Y. F. Huang, D. M. Jiang, and Y. N. Zhang. "*Accurate EEG-based emotion recognition on combined features using deep convolutional neural networks*." IEEE Access 7 (2019): 44317-44328.

[3] Abiyev, Rahib, Murat Arslan, John Bush Idoko, Boran Sekeroglu, and Ahmet Ilhan. "*Identification of epileptic EEG signals using convolutional neural networks*." Applied Sciences 10, no. 12 (2020): 4089.

[4] Song, Tengfei, Wenming Zheng, Peng Song, and Zhen Cui. "*EEG emotion recognition using dynamical graph convolutional neural networks*." IEEE Transactions on Affective Computing 11, no. 3 (2018): 532-541.

[5] Liu, Chien-Liang, Bin Xiao, Wen-Hoar Hsaio, and Vincent S. Tseng. "*Epileptic seizure prediction with multi-view convolutional neural networks*." IEEE Access 7 (2019): 170352-170361.

[6] Usman, Syed Muhammad, Muhammad Usman, and Simon Fong. "*Epileptic seizures prediction using machine learning methods*." Computational and mathematical methods in medicine 2017 (2017).

[7] Li, Gen, Chang Ha Lee, Jason J. Jung, Young Chul Youn, and David Camacho. "*Deep learning for EEG data analytics: A survey*." Concurrency and Computation: Practice and Experience 32, no. 18 (2020): e5199.

[8] Mao, W. L., Fathurrahman, H. I. K., Lee, Y., & Chang, T. W. (2020). "*EEG dataset classification using CNN method*". In *Journal of physics: conference series* (Vol. 1456, No. 1, p. 012017). IOP Publishing.

[9] Yang, Heekyung, Jongdae Han, and Kyungha Min. "*A multi-column CNN model for emotion recognition from EEG signals*." Sensors 19, no. 21 (2019): 4736.

[10] Shoeb, J. Guttag, "*Application of machine learning to epileptic seizure onset detection*", in: 27th International Conference on Machine Learning (ICML),June 21–24, Haifa, Israel, 2010.

[11] Q. Lin, S. Ye, C. Wu, W. Gu, Y. Xue, "*A novel framework based on bi-clustering for automatic epileptic seizure detection*", Int. J. Mach. Learn. Cybernet. 10(2017) 1–13.

[12] T. Zhang, W.Z. Chen, "*LMD Based Features for the Automatic Seizure Detection of EEG Signals Using SVM*", IEEE Trans. Neural Syst. Rehab. Eng. 25 (8) (2017)1100–1108.

[13] A.Bhattacharyya, M. Sharma, R.B. Pachori, P. Sircar, U.R. Acharya, "*A novel approach for automated detection of focal EEG signals using empirical wavelet transform*", Neural Computing and Applications 29.8 (2018): 47-57.

[14] Kiranyaz, Serkan, Turker Ince, Morteza Zabihi, and Dilek Ince. "*Automated patient-specific classification of long-term electroencephalography*." Journal of biomedical informatics 49 (2014): 16-31.

[15] Turky N. Alotaiby, Saleh A. Alshebeili, Faisal M. Alotaibi, Saud R. Alrshoud, "*Epileptic Seizure Prediction Using CSP and LDA for Scalp EEG Signals*", Computational Intelligence and Neuroscience, vol. 2017, Article ID 1240323, 11 pages, 2017.

[16] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "*Imagenet classification with deep convolutional neural networks*." Advances in neural information processing systems 25 (2012): 1097-1105.

[17] Sharma, Rajeev, Ram Bilas Pachori, and Abhay Upadhyay. "*Automatic sleep stages classification based on iterative filtering of electroencephalogram signals*." Neural Computing and Applications 28.10 (2017): 2959-2978.

[18] Acharya, U. Rajendra, Shu Lih Oh, Yuki Hagiwara, Jen Hong Tan, and Hojjat Adeli. "*Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals*." Computers in biology and medicine 100 (2018): 270-278.

[19] Hou, Yimin, Lu Zhou, Shuyue Jia, and Xiangmin Lun. "*A novel approach of decoding EEG four-class motor imagery tasks via scout ESI and CNN*." Journal of neural engineering 17, no. 1 (2020): 016048.

[20] Emami, Ali, Naoto Kunii, Takeshi Matsuo, Takashi Shinozaki, Kensuke Kawai, and Hirokazu Takahashi. "*Seizure detection by convolutional neural network-based analysis of scalp electroencephalography plot images*." NeuroImage: Clinical 22 (2019): 101684.

[21] Mao, W. L., H. I. K. Fathurrahman, Y. Lee, and T. W. Chang. "*EEG dataset classification using CNN method*." In Journal of physics: conference series, vol. 1456, no. 1, p. 012017. IOP Publishing, 2020.

[22] Cooney, Ciaran, Raffaella Folli, and Damien Coyle. "*Optimizing layers improves CNN generalization and transfer learning for imagined speech decoding from EEG*." In 2019 IEEE international conference on systems, man and cybernetics (SMC), pp. 1311-1316. IEEE, 2019.

[23] Ma, Lan, James W. Minett, Thierry Blu, and William SY Wang. "*Resting state EEG-based biometrics for individual identification using convolutional neural networks*." In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2848-2851. IEEE, 2015.

[24] Acharya, U. Rajendra, et al. "*Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals*." *Computers in biology and medicine* 100 (2018): 270-278.

[25] Hou, Yimin, et al. "*A novel approach of decoding EEG four-class motor imagery tasks via scout ESI and CNN*." *Journal of neural engineering* 17.1 (2020): 016048.

[26] Cooney, Ciaran, Raffaella Folli, and Damien Coyle. "*Optimizing layers improves CNN generalization and transfer learning for imagined speech decoding from EEG*." *2019 IEEE*