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# Seizure stage detection of epileptic seizure using convolutional neural networks

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**ABSTRACT**

According to the World Health Organization (WHO), seventy million individuals worldwide suffer from epilepsy, a neurological disorder. While electroencephalography (EEG) is crucial for diagnosing epilepsy and monitoring the brain activity of epilepsy patients, it requires a specialist to examine all EEG recordings to find epileptic behavior. This procedure needs an experienced doctor, and a precise epilepsy diagnosis is crucial for appropriate treatment. To identify epileptic seizures, this study employed a convolutional neural network (CNN) based on raw scalp EEG signals to discriminate between preictal, ictal, postictal, and interictal segments. The possibility of these characteristics is explored by examining how well time-domain signals work in the detection of epileptic signals using intracranial Freiburg Hospital (FH), scalp Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) databases, and Temple University Hospital (TUH) EEG. To test the viability of this approach, two types of experiments were carried out. Firstly, binary class classification (preictal, ictal, postictal each versus interictal) and four-class classification (interictal versus preictal versus ictal versus postictal). The average accuracy for stage detection using CHB-MIT database was 84.4%, while the Freiburg database's time-domain signals had an accuracy of 79.7% and the highest accuracy of 94.02% for classification in the TUH EEG database when comparing interictal stage to preictal stage.



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## 1. INTRODUCTION

The defining feature of epilepsy is recurrent seizures brought on by irregular electrical discharges in the brain resulting in unconscious behavioral alterations including convolutions and loss of awareness [1], [2]. Of the 80% of epileptic patients in low- and middle-income nations, three-fourths experience a lack of anti-seizure medications or a gap in their therapy. Because of this, epileptic episodes can occur suddenly and often, which makes diagnosis and treatment challenging. Preictal, ictal, postictal, and interictal are the four stages of a seizure. Preictal occurs shortly prior to an epileptic seizure; ictal is the seizure's onset period; post-ictal occurs immediately following the ictal and lasts for up to ten minutes; and interictal occurs after around ten minutes of onset and continues until the next seizure occurs. Preictal symptoms include headache, nausea, and dizziness. The ictal area of the brain experiences high electrical activity after this stage. The postictal phase follows, during which the patient regains baseline symptoms and experiences symptoms such as headache, fatigue, and vertigo.

Classifying patients into two main categories: i) seizure-free individuals and ii) distinct types of seizures-is now feasible because to the development of machine learning and deep learning, although this is done during the ictal period. Classification is slightly easier when using a high-frequency electroencephalography (EEG) output that includes spikes. There is a significant amount of study on the ictal stage available in the literature, but not in the pre-, post-, or interictal stages.

This section focuses on multiple studies present in the literature that are based on stage detection, including ictal, preictal, interictal, postictal, sleep stage, and mental state. In study [3], [4], the epileptic episode in the EEG signals was automatically identified using a radial basis function (RBF) kernel and a least squares support vector machine (SVM) classifier. From the recorded EEG signal, the normal stage, ictal stage, and interictal stage can be identified here. Generalized retrospective method was adopted by researcher where long short-term memory (LSTMs) and convolutional neural networks (CNNs) were used as classifier for hybrid models considering PatientWise details in [5]–[7]. Nine connectivity aspects have been investigated in total, based on five different metrics in the time, frequency, and time-frequency domains. The K-nearest neighbor (KNN) algorithm has validated the solution by distinguishing an epilepsy group (EG) against a healthy control (HC). Afterward, a psychogenic kind of disease was tested using another group of patients characterized by non-epileptic disorder (NEAD) [8], [9].

Because EEG signals are chaotic and nonlinear, entropy-based techniques [10], [11] are frequently employed for the classification of seizures. Seizures are detected using two entropy features: i) multiscale dispersion entropy (MDE) and ii) refined composite multiscale dispersion entropy (RCMDE). The capacity of MDE and RCMDE to separate epilepsy patients' ictal (during seizures) and interictal (between episodes) EEGs from EEGs of non-epileptic subjects. When attempting to classify sleep phases from single-channel EEG data using statistical variables in the time domain, six distinct sleep stages were identified by combining structural graph similarity and K-means analysis. This technique effectively extracts features without signal preprocessing [12]–[14]. Whereas study in [15]–[17], investigates the feasibility of utilizing frontal and central electrodes for tiredness detection, posterior alpha band and frontal beta band activity for dissatisfaction detection, and posterior alpha band activity for attention detection for feature extraction in a passive brain-computer interface. EEG is used on a single-trial basis towards monitoring mental state. Where the dual-tree is classified using complex wavelet transform approach against low levels of supervised training up to the sixth level utilizing time-frequency subbands [18].

During clinical intervention, non-invasive EEG signal recording is used for the majority of this type of study. However, the data of patients receiving invasive video EEG monitoring (VEM) were retrospectively reviewed [19]–[21]. Included in the data were cases in which the brain region responsible for inducing electrically induced seizures (EIS) was removed and at least one spontaneously occurring habitual seizure (SHS) occurred during VEM. After surgical intervention, follow-up (FU) visits were conducted trice (1, 2 years, and the latest FU) to assess seizure outcome in accordance with the international league against epilepsy (ILAE) and Engel.

In [22]–[24] used a combination of seven different classifiers, namely SVM, decision tree (DT) the fuzzy surgeon classifier (FSC), KNN, Gaussian mixture models (GMM), probabilistic neural network, and nave Bayes (NB), to differentiate between a patient's three stages of “normal”, “preictal”, and “ictal”. With preprocessed data, several classifiers were used in [25], [26] namely KNN, SVM, a polynomial classifier, logistic model tree (LMT), an uncorrelated normal density-based classifier (UDC), DT. The preprocessing techniques adopted are as follows: entropy, variance, skewness, and root mean square (RMS). A statistical sampling strategy called optimal sample allocation methodology was proposed [27], and a feature selection algorithm was created towards decreasing the features. For the investigation, five classifiers were combined: SVM, KNN, NB, LMT, and random forest (RF).

SVM, KNN, RF, and AdaBoost were the four classifiers used [28] on a dataset with high-dimensional data comprised of 28 features. Where results showed that the SVM performs better than the cubic kernel. SVM and RF were used by [28] using the dataset created by ten characteristics of time and frequency domain. The three distinct seizure stages i.e. “preictal,” “ictal,” and “interictal” seizures were classified with 100% accuracy using KNN, artificial neural networks (ANN), SVM, and RF as classifiers. These classifiers were applied to two well-known datasets: Fitchburg Hospital (FH) and Children's Hospital Boston-Massachusetts institute of technology (CHB-MIT) [29]. In [30], [31] proposed an automated method using RF and iterative filtering to identify the EEG signals. This classification accuracy for D versus E was 96%, E versus ABCD was 98.4%, and 99.5% for the a against E subsets using the Bonn University dataset (A-E). The “seizure” versus “non-seizure” classes are distinguished using KNN, and the important channels are investigated using random forest, as stated in [32].

From the literature survey it is noted that, automatic seizure detection plays vital role towards epilepsy treatment. Many works explained the role of machine and deep learning models in seizure diagnostic. Towards protecting the epileptic patients from sudden fall or understanding the condition of the patients, it is important to detect and predict the stage of seizure. Though in the recent past, few work focused on seizure stage prediction but classification of all stages with raw EEG data is not considered. Moreover, most of the research work mainly focused on seizure free prediction and seizure type prediction in the ictal stage. Very less attention paid for preictal, postictal and interictal stages. Preictal stage prediction is very important towards patient's safety. Whereas detection of post ictal can help to understand the frequency of occurrence of seizure and it is duration of disturbance after the episode. Since most of the outpatients consult clinician only in interictal stage, so classification of interictal stage can aid diagnostic of epileptic seizure. Recently few researchers used preictal and interictal stages for experimentation, but after preprocessing the EEG signals using various mathematical models. Since EEG is a very sensitive signal, there is a chance of losing information during pre-processing.

Thus, using raw EEG signals and CNN models, prediction and categorization of all four stages are taken into consideration in this research work. Three datasets are employed in this work: FH, CHB-MIT, and Temple University Hospital (TUH) EEG. TUHEEG is partitioned for four phases, in this study, while the FH and CHB-MIT datasets are partitioned at source. The CNN model is developed and validated using three datasets in order to extract features and classify the four different stages from raw EEG signals. The second section discusses the methodology. Section 3 discusses results in detail followed by section 4 dealing with conclusion.

## 2. METHOD

In this section the methodology adopted for this work is discussed in details. To predict different stages of seizure, the CNN algorithm is used. It is trained to classify preictal, ictal, postictal, and interictal stages using three EEG datasets are carried out.

### 2.1. Dataset

In this section, the dataset used for stage prediction is discussed. To check model performance and validate CNN model three EEG datasets are used. They are namely FH, CHB-MIT and TUHEEG datasets. In FH and CHB-MIT, data of different stages are available for use, whereas TUHEEG data is self-partitioned, and four stages dataset is created.

#### 2.1.1. Freiburg Hospital dataset

This dataset was created by the Epilepsy Center (EC) at the University Hospital of Freiburg based on data collected from 21 patients with focal epilepsy. Here intracranial EEG (iEEG) recordings with 128 channels a 256 Hz sampling rate are used. The digital video EEG were acquired with a Neurofile Nortriptyline (NT), a 16-bit analogue-to-digital converter system. Records of 87 seizures from 21 patients, all of whom had two to five seizures throughout the study are included in the collection. Skilled epileptologists visually examined the iEEG data for each patient in this database to select six contacts: three in the immediate vicinity of the epileptic zone and three in more distant locations implicated in seizure propagation and spread. The age group considered from 10 to 50, with 13 women and 8 men. At least two of the patients suffered focal seizure (FNSz), complex partial seizure (CPSz), or generalized tonic-clonic seizure (GTCSz) seizures. In neocortical brain areas, around eleven patients have epileptic focus, whereas eight patients had in hippocampus, and two patients had both the areas. The Epilepsy Center's board-certified epileptologists annotated the epileptiform activities and seizure onset times.

#### 2.1.2 Children's Hospital Boston-M Institute of Technology dataset

It is an open-source EEG database with 23 epileptic children information, where scalp electrodes were used to record the data. The study included 17 female participants with ages ranging from 1.5 to 19 years and 5 boys with 3 to 22 years age group. The sexual orientation and age of one child were overlooked. All were instructed to stop using relevant drugs one week prior to data collection. There are 23 pediatric patients in the dataset, and they have 844 hours of continuous EEG recording of 163 seizures. The majority of the scalp EEG data were recorded with 256 Hz sampling rate. Each individual had varying numbers and durations of seizures, and the begin and end periods of each seizure are clearly labeled based on expert assessments.

Many segments were selected for the purpose of detecting preictal, ictal, postictal, and interictal signals for these two publicly available datasets. In this work, raw recordings were divided into 1-s epochs using the moving-window technique, and each patient's differences were evaluated by applying CNN. Predicting the preictal, ictal, postictal, and interictal stages is the primary goal of this work.

### 2.1.3. Temple University Hospital EEG dataset

In this case, the generalized seizure (GNSZ) seizure dataset is considered. Here, EEG recordings taken 100 seconds before the start time of onset for the preictal period and 100 seconds after 10 minutes of the stop time of onset for the interictal period are considered. The data collected from TUHEEG corpus for Preictal, ictal, post ictal and interictal stages are as follows. The number of events considered 54,39, 51, and 44 where samples collected 723400, 733780, 725600 and 737000 for preictal, ictal, post ictal and inter ictal respectively.

## 2.2. Implementation of convolutional neural networks

CNN model with 4 layers is designed. Each convolution layer has 32 filters maps with 3×3 kernel size. The summary of the CNN model shown in Table 1. The layers from conv2d_1 to conv2d_4 represent four convolution layers followed by four maxpool layer represented by maxpool2d_1.to maxpool2d_4. Output shape represents the shape of output or activation maps after each operation. The calculation of output of convolution layer is done using (1).

$$Output = (input - kernel\ size + 2 \times padding)/stride + 1 \tag{1}$$

For 3×3 kernel size with padding=1, the output shape of the layer is (124, 124, 32), where each convolution layer has 32 filters. For the first convolutional layer the calculation of parameters are done using (2).

$$Number\ of\ parameter\ in\ convolution\ layer = ((S_k \times F_p) + 1) \times F_c \tag{2}$$

Where, $S_k$=kernel size, $F_p$=previous layer filters, $F_c$= current layer filters, Parameter in 1st convolution layer = ((3×3×3)+1)×32=896

Table 1. CNN implementation model details

| Type of Layer | Shape of the output | Parameter | Type of Layer | Shape of the output | Parameter |
|---|---|---|---|---|---|
| Conv2d_1 | (None, 124, 124, 32) | 896 | Activation_4 | (None, 12, 12, 32) | 0 |
| Activation_1 | (None, 124, 124, 32) | 0 | Max_pooling2d_4 | (None, 6, 6, 32) | 0 |
| Maxpool2d_1 | (None, 62, 62, 32) | 0 | Flatten_1 | (None, 1152) | 0 |
| Conv2d_2 | (None, 60, 60, 32) | 9248 | Dense_1 | (None, 511) | 589825 |
| Activation_2 | (None, 60, 60, 32) | 0 | Activation_5 | (None, 511) | 0 |
| Max_pooling2d_2 | (None, 30, 30, 32) | 0 | Dropout_1 | (None, 511) | 0 |
| Conv2d_3 | (None, 28, 28, 32) | 9248 | Dense_2 | (None, 32) | 16985 |
| Activation_3 | (None, 28, 28, 32) | 0 | Activation_6 | (None, 32) | 0 |
| Max_pooling2d_3 | (None, 14, 14, 32) | 0 | Dropout_2 | (None, 32) | 0 |
| Conv2d_4 | (None, 12, 12, 32) | 9248 | Dense_3 | (None ,1) | 33 |

The algorithms used to extract features and classify using a typical CNN model are as follows.

Step 1: Input image (two dimensional) dataset is fed into the network.
Step 2: Convolutional layers perform dot products between the input image and a set of filters to produce feature maps. The filters are then shifted across the image to cover all possible locations.
Step 3: To reduce the spatial dimensions the feature map is down sampled in pooling layers and increase the robustness to small translations in the input.
Step 4: Fully connected layers perform a dot product between the feature maps and a set of weights to produce the final prediction.
Step 5: Using the back propagation technique, the weights are changed by measuring the difference between the ground truth labels and the predictions using the loss function.
Step 6: The above steps are repeated for multiple epochs until convergence or a stopping criterion is met.

Max pooling operation reduces the size up to 62 pixels using 2×2 window with a stride of 2. The learnable parameters in pooling layer are zero. Similarly, second, third and fourth convolutional layer parameters are calculated using 3×3 filters and with padding = 0.

The highest number of parameters are present in fully connected layer as every neuron is connected to each other. It can be calculated by the product of number of neurons in current layer ($N_c$) and number of neurons in the previous layer ($N_p$) with a bias term is as in (3). These layers are followed by a flattening. There are three dense layer and two dropout layers are considered. Here, dropout-rate p is the number of hyperparameter. For 50% of the neurons being dropped out $p = 0.5$ is set. Figure 1 CNN model with layer wise calculations. The class labels obtained after passing 511×511 input image dataset through classification algorithm.

$$Number\ of\ parameters\ in\ fully\ connected\ layer = ((N_c\ x\ N_p) + 1\ x\ N_c) \quad (3)$$

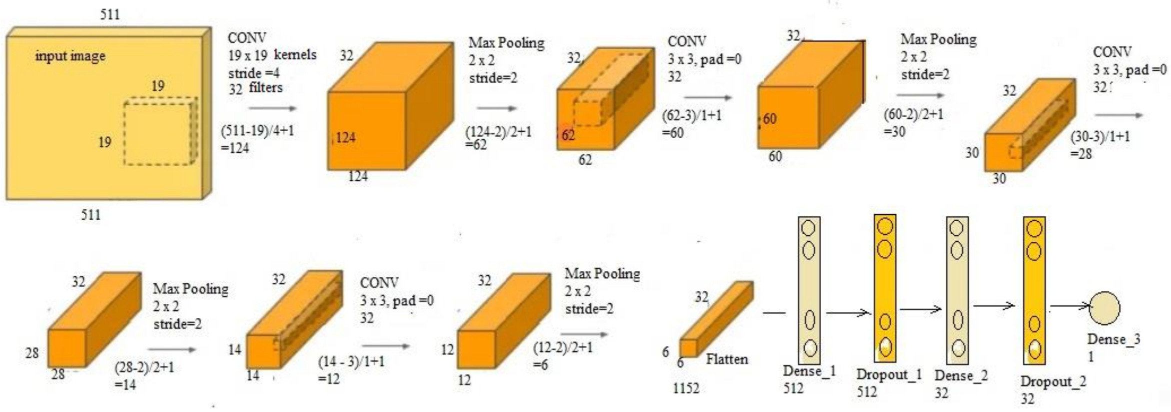


Figure 1. CNN model with layer wise calculations

## 3. RESULTS AND DISCUSSION

In this experimentation, three binary class classification and one four class classification is considered for three datasets, i.e. FH, CHB-MIT and TUHEEG. The three datasets considered in raw form i.e. without any pre-processing to avoid losing any information from EEG signals. The results obtained by each dataset are discussed in detail in the preceding sub sections.

### 3.1. Result obtained for Freiburg Hospital dataset

Table 2 describes the performance of CNN model in the FH database. A total of 13 patients (PAT) results are noted and the average of all the patients for three binary classes i.e. preictal versus interictal, ictal versus interictal and postictal versus interictal are 79.7%, 93.69%, and 83.85% respectively. Out of 13 patients, model shows satisfactory performance for nine patients, but patient numbers 5,14,19,20 shows 60%, 25%, 25% and 60% accuracy for preictal versus interictal classification. However, patient numbers 1, 3, 6, 15, 18, 21 shows 100% accuracy for all the three binary classification methods.

Table 2. Seizure prediction results using FH EEG dataset and CHB-MIT EEG dataset

| FH | | | | | | CHB-MIT | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Patient | No. of seizure | No. of Hours | Acc(%) Preictal Vs Interictal | Acc(%) Ictal Vs Interictal | Acc(%) Postictal Vs Interictal | Patients | No. of seizure | No. of Hours | Acc(%) Preictal Vs Interictal | Acc(%) ictal Vs Interictal | Acc(%) Postictal Vs Interictal |
| PAT1 | 4 | 23.9 | 100 | 100 | 100 | PAT1 | 7 | 17 | 100 | 100 | 100 |
| PAT3 | 5 | 23.9 | 100 | 100 | 100 | PAT2 | 3 | 22.9 | 33 | 78.5 | 45.5 |
| PAT4 | 5 | 23.9 | 100 | 100 | 90 | PAT3 | 6 | 21.9 | 100 | 100 | 98.5 |
| PAT5 | 5 | 23.9 | 60 | 90 | 68 | PAT5 | 5 | 13 | 80 | 90.5 | 81.6 |
| PAT6 | 3 | 23.8 | 100 | 100 | 100 | PAT9 | 4 | 12.3 | 50 | 75.2 | 60.2 |
| PAT14 | 4 | 22.6 | 25 | 85 | 56 | PAT10 | 6 | 11.1 | 67 | 90.4 | 70.7 |
| PAT15 | 4 | 23.7 | 100 | 98 | 100 | PAT13 | 5 | 14 | 80 | 98.5 | 85.4 |
| PAT16 | 5 | 23.9 | 80 | 80 | 78 | PAT14 | 5 | 5 | 60 | 79.5 | 70.1 |
| PAT17 | 5 | 24 | 80 | 100 | 80 | PAT18 | 6 | 23 | 100 | 100 | 98.4 |
| PAT18 | 5 | 24.8 | 100 | 100 | 100 | PAT19 | 3 | 24.9 | 100 | 100 | 100 |
| PAT19 | 4 | 24.3 | 25 | 75 | 48 | PAT20 | 5 | 20 | 100 | 99.5 | 100 |
| PAT20 | 5 | 24.8 | 60 | 90 | 70 | PAT21 | 4 | 20.9 | 100 | 96.8 | 99.2 |
| PAT21 | 5 | 23.9 | 100 | 100 | 100 | PAT23 | 5 | 3 | 100 | 100 | 100 |
| TOTAL | 59 | 311.4 | 79.7 | 93.6 | 83.85 | TOTAL | 64 | 311.4 | 84.4 | 93.01 | 85.38 |

### 3.2. Result obtained for TUHEEG dataset

The performance of CNN model in the TUHEEG database for a total of 18 patients' information are as follows. The three binary class classifications result 92.04%, 98.56% and 93.33% for preictal versus interictal, ictal versus interictal and postictal versus interictal respectively. These binary classes used the total number of events as 98,85 and 95.

The mathematical formula for calculating accuracy, precision, sensitivity, F1 score, and each class accuracy is shown in (4) to (8) respectively.

$$Over\ all\ accuracy = (TP\ + TN)/\ (TP + TN + FP + FN) \tag{4}$$

$$Precision = TP/(TP + FP) \tag{5}$$

$$Sensitivity = TP/(TP + FN) \tag{6}$$

$$F1\ score = TP/(TP +\ 0.5 \times\ (FN + FP)) \tag{7}$$

$$Class\ accuracy =\ TP/(TP + FN) \tag{8}$$

where $TP$ is true positive, $TN$ is true negative.

Table 3 describes accuracy, precision, sensitivity and F1 score of binary seizure stage prediction using CNN model of three datasets for preictal versus interictal, ictal versus interictal, and postictal versus interictal respectively.

Table 3. Performance of prediction of preictal vs interictal, ictal vs interictal and postictal vs interictal

| | | Preictal Vs Interictal | | | Ictal Vs Interictal | | | Postictal Vs Interictal | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dataset | Matrix | Acc(%) Preictal | Acc(%) Interictal | Acc(%) Mean | Acc(%) ictal | Acc(%) Interictal | Acc(%) Mean | Acc(%) Postictal | Acc(%) Interictal | Acc(%) Mean |
| FH | Accuracy | 80.0 | 79.4 | 79.7 | 90.9 | 96.15 | 93.69 | 84.61 | 81.81 | 83.85 |
| | Precision | 74.07 | 84.37 | 79.22 | 96.77 | 89.28 | 93.02 | 78.57 | 87.09 | 82.83 |
| | Sensitivity | 80.0 | 79.4 | 79.7 | 90.9 | 96.15 | 93.69 | 84.61 | 81.81 | 83.85 |
| | F1 Score | 0.769 | 0.842 | 0.805 | 0.937 | 0.933 | 0.935 | 0.814 | 0.843 | 0.829 |
| CHBMIT | Accuracy | 88.89 | 81.08 | 84.4 | 96.96 | 91.17 | 93.01 | 89.28 | 83.33 | 85.38 |
| | Precision | 77.42 | 90.09 | 83.75 | 90.62 | 96.87 | 93.74 | 80.64 | 90.9 | 85.77 |
| | Sensitivity | 88.89 | 81.08 | 84.4 | 96.96 | 91.17 | 93.01 | 89.28 | 83.33 | 85.38 |
| | F1 Score | 0.827 | 0.857 | 0.842 | 0.935 | 0.939 | 0.937 | 0.847 | 0.869 | 0.858 |
| TUHEEG | Accuracy | 90.9 | 93.02 | 92.04 | 100 | 97.82 | 98.56 | 95.65 | 91.83 | 93.33 |
| | Precision | 94.33 | 88.89 | 91.60 | 97.5 | 100 | 98.75 | 91.66 | 95.74 | 93.7 |
| | Sensitivity | 90.9 | 93.02 | 92.04 | 100 | 97.82 | 98.56 | 95.65 | 91.83 | 93.33 |
| | F1 Score | 0.925 | 0.909 | 0.917 | 0.987 | 0.989 | 0.988 | 0.936 | 0.937 | 0.937 |

Whereas the trains accuracies of three datasets for four class classification i.e., preictal versus ictal versus postictal versus interictal are 78.7%, 86.0%, 95.08% for FH, CHB-MIT and TUHEEG dataset respectively. The test accuracies are 79.7%, 84.4% and 94.02% for FH, CHB-MIT and TUHEEG dataset respectively. For this experimentation, train –test ratio is considered as 80:20. Out of train data, 10% is used for validation.

From the above it can be observed that, the performance of developed CNN model with all the three datasets are comparable and accuracy varies from 79.7% to 92.04% in case of preictal versus interictal binary classifications. The accuracy varies from 93.69% to 98.56% in the case of ictal versus interictal binary classification. The accuracy varies from 83.85% to 93.33% in case of postictal versus interictal binary classifications. Whereas, for four class classification lowest and highest test accuracy achieved 79.7% and 94.02% respectively. It can be noted, in all the cases, FH shows lowest accuracy and TUHEEG shows highest accuracies. The reason might be self-partitioning the datasets in the case of TUHEEG.

## 4. CONCLUSION

Currently, a variety of conventional and cutting-edge technologies are generally used to assess epileptic activity in EEG recordings. A speedier diagnosis, ongoing monitoring, and a decrease in the overall cost of medical care are just a few benefits of automating this procedure. In this work, a very straightforward CNN structure is used to avoid the challenging feature extraction procedure. To verify the efficacy of the model, the Freiburg, CHB-MIT and TUHEEG datasets are examined. The CNN algorithm is used in FH, CHB-MIT, and TUHEEG datasets with 32 specified filters in the Conv2D layer, so the actual output shape is (124, 124, 32) for each input image. The overall accuracy of four class classification is 79.7%, 84.4%, and 94.02% for the FH, CHB-MIT, and TUHEEG datasets, respectively. All three datasets are trained and tested at an 80:20 ratio. Epileptic EEG signals from all three datasets, preictal, ictal, postictal, and interictal stages-have been extracted. The CNN model is used to predict preictal, ictal, postictal, and interictal stages.

In future, detection of seizure- non seizure in all the for stages can be done. Which can aid treatment by relating history with model diagnosis. The diagnosis of different types of seizure in mainly interictal stage a help to a large extend to clinical to prescribe proper anti-seizure drugs.

## REFERENCES


[1] Z. Souirti *et al.*, "Prevalence of epilepsy in Morocco: a population-based study," *Epilepsia Open*, vol. 8, no. 4, pp. 1340–1349, Oct. 2023, doi: 10.1002/epi4.12802.

[2] K. K. Dutta, "Epilepsy is a curse: Myth or Reality," *InnoHEALTH magazine digital team*, Oct. 2020. https://innohealthmagazine.com/2020/issues/epilepsy-is-a-curse-myth-or-reality/ (accessed Jul. 11, 2023).

[3] S. Madhavan, R. K. Tripathy, and R. B. Pachori, "Time-frequency domain deep convolutional neural network for the classification of focal and non-focal EEG signals," *IEEE Sensors Journal*, vol. 20, no. 6, pp. 3078–3086, Mar. 2020, doi: 10.1109/JSEN.2019.2956072.

[4] A. Anuragi, D. Singh Sisodia, and R. B. Pachori, "Epileptic-seizure classification using phase-space representation of FBSE-EWT based EEG sub-band signals and ensemble learners," *Biomedical Signal Processing and Control*, vol. 71, Jan. 2022, doi: 10.1016/j.bspc.2021.103138.

[5] W. Hussain, M. T. Sadiq, S. Siuly, and A. U. Rehman, "Epileptic seizure detection using 1 D-convolutional long short-term memory neural networks," *Applied Acoustics*, vol. 177, Jun. 2021, doi: 10.1016/j.apacoust.2021.107941.

[6] T. Tuncer, S. Dogan, G. R. Naik, and P. Pławiak, "Epilepsy attacks recognition based on 1D octal pattern, wavelet transform and EEG signals," *Multimedia Tools and Applications*, vol. 80, no. 16, pp. 25197–25218, Apr. 2021, doi: 10.1007/s11042-021-10882-4.

[7] S. Raghu, N. Sriraam, Y. Temel, S. V. Rao, and P. L. Kubben, "EEG based multi-class seizure type classification using convolutional neural network and transfer learning," *Neural Networks*, vol. 124, pp. 202–212, Apr. 2020, doi: 10.1016/j.neunet.2020.01.017.

[8] J. Cao *et al.*, "Using interictal seizure-free EEG data to recognise patients with epilepsy based on machine learning of brain functional connectivity," *Biomedical Signal Processing and Control*, vol. 67, May 2021, doi: 10.1016/j.bspc.2021.102554.

[9] K. K. Dutta, P. Manohar, I. K, F. Naaz, M. Lakhminarayanan, and S. Rajagopalan, "Seven Epileptic Seizure type classification in pre-ictal, ictal and inter-ictal stages using machine learning techniques," Preprint, *Research Square*, 2022, doi: 10.21203/rs.3.rs-2100432/v1.

[10] Sukriti, M. Chakraborty, and D. Mitra, "Automated detection of epileptic seizures using multiscale and refined composite multiscale dispersion entropy," *Chaos, Solitons and Fractals*, vol. 146, May 2021, doi: 10.1016/j.chaos.2021.110939.

[11] K. K. Dutta, K. Venugopal, and S. A. Swamy, "Removal of muscle artifacts from EEG based on ensemble empirical mode decomposition and classification of seizure using machine learning techniques," in *2017 International Conference on Inventive Computing and Informatics (ICICI)*, Nov. 2017, pp. 861–866, doi: 10.1109/ICICI.2017.8365259.

[12] M. Diykh, Y. Li, and P. Wen, "EEG sleep stages classification based on time domain features and structural graph similarity," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 11, pp. 1159–1168, Nov. 2016, doi: 10.1109/TNSRE.2016.2552539.

[13] A. K. Jaiswal and H. Banka, "Local pattern transformation based feature extraction techniques for classification of epileptic EEG signals," *Biomedical Signal Processing and Control*, vol. 34, pp. 81–92, Apr. 2017, doi: 10.1016/j.bspc.2017.01.005.

[14] R. Sharma and R. B. Pachori, "Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions," *Expert Systems with Applications*, vol. 42, no. 3, pp. 1106–1117, Feb. 2015, doi: 10.1016/j.eswa.2014.08.030.

[15] A. Myrden and T. Chau, "A passive EEG-BCI for single-trial detection of changes in mental state," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 4, pp. 345–356, Apr. 2017, doi: 10.1109/TNSRE.2016.2641956.

[16] S. Patidar and T. Panigrahi, "Detection of epileptic seizure using Kraskov entropy applied on tunable-Q wavelet transform of EEG signals," *Biomedical Signal Processing and Control*, vol. 34, pp. 74–80, Apr. 2017, doi: 10.1016/j.bspc.2017.01.001.

[17] A. Bhattacharyya, R. Pachori, A. Upadhyay, and U. Acharya, "Tunable-Q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals," *Applied Sciences*, vol. 7, no. 4, Apr. 2017, doi: 10.3390/app7040385.

[18] P. Swami, T. K. Gandhi, B. K. Panigrahi, M. Tripathi, and S. Anand, "A novel robust diagnostic model to detect seizures in electroencephalography," *Expert Systems with Applications*, vol. 56, pp. 116–130, Sep. 2016, doi: 10.1016/j.eswa.2016.02.040.

[19] C. Kämpfer, A. Racz, C. M. Quesada, C. E. Elger, and R. Surges, "Predictive value of electrically induced seizures for postsurgical seizure outcome," *Clinical Neurophysiology*, vol. 131, no. 9, pp. 2289–2297, Sep. 2020, doi: 10.1016/j.clinph.2020.06.013.

[20] M. Li, W. Chen, and T. Zhang, "Automatic epileptic EEG detection using DT-CWT-based non-linear features," *Biomedical Signal Processing and Control*, vol. 34, pp. 114–125, Apr. 2017, doi: 10.1016/j.bspc.2017.01.010.

[21] A. Zarei and B. M. Asl, "Automatic seizure detection using orthogonal matching pursuit, discrete wavelet transform, and entropy based features of EEG signals," *Computers in Biology and Medicine*, vol. 131, Apr. 2021, doi: 10.1016/j.compbiomed.2021.104250.

[22] K. K. Dutta, P. Manohar, S. Rajagopalan, F. Naaz, and M. Lakshminarayanan, "Eye state detection from electro-encephalography signals using machine learning techniques," in *2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon)*, Oct. 2022, pp. 1–7, doi: 10.1109/MysuruCon55714.2022.9972567.

[23] A. Sasidharan and K. K. Dutta, "Application of machine-learning techniques in electroencephalography signals," in *Brain and Behavior Computing*, CRC Press, 2021.

[24] M. S. Farooq, A. Zulfiqar, and S. Riaz, "Epileptic seizure detection using machine learning: taxonomy, opportunities, and challenges," *Diagnostics*, vol. 13, no. 6, Mar. 2023, doi: 10.3390/diagnostics13061058.

[25] K. K. Dutta, P. Manohar, and K. Indira, "Time and frequency domain pre-processing for epileptic seizure classification of epileptic EEG signals," *Journal of Intelligent and Fuzzy Systems*, vol. 45, no. 5, pp. 8217–8226, Nov. 2023, doi: 10.3233/jifs-224570.

[26] K. Indira, K. K. Dutta, S. Poornima, and S. A. S. Bellary, "Deep learning methods for data science," *Advanced Analytics and Deep Learning Models*. Wiley, pp. 151–179, May 2022, doi: 10.1002/9781119792437.ch7.

[27] M. Mursalin, S. S. Islam, M. K. Noman, and A. A. Al-Jumaily, "Epileptic seizure classification using statistical sampling and a novel feature selection algorithm," *arXiv:1902.09962*, 2019.

[28] S. Raghu and N. Sriraam, "Classification of focal and non-focal EEG signals using neighborhood component analysis and machine learning algorithms," *Expert Systems with Applications*, vol. 113, pp. 18–32, Dec. 2018, doi: 10.1016/j.eswa.2018.06.031.

[29] F. Manzouri, S. Heller, M. Dümpelmann, P. Woias, and A. Schulze-Bonhage, "A comparison of machine learning classifiers for energy-efficient implementation of seizure detection," *Frontiers in Systems Neuroscience*, vol. 12, Sep. 2018, doi: 10.3389/fnsys.2018.00043.

[30] S. Sari, T. Sutikno, I. Soesanti, and N. A. Setiawan, "A review of convolutional neural network-based computer-aided lung nodule detection system," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 3, pp. 1044–1061, Sep. 2023, doi: 10.11591/ijai.v12.i3.pp1044-1061.

[31] T. Tuncer, S. Dogan, and U. Rajendra Acharya, "Automated EEG signal classification using chaotic local binary pattern," *Expert Systems with Applications*, vol. 182, Nov. 2021, doi: 10.1016/j.eswa.2021.115175.

[32] A. Y. Saleh and C. K. Chin, "Development of hybrid convolutional neural network and autoregressive integrated moving average on computed tomography image classification," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 4, pp. 1864–1872, Dec. 2023, doi: 10.11591/ijai.v12.i4.pp1864-1872.


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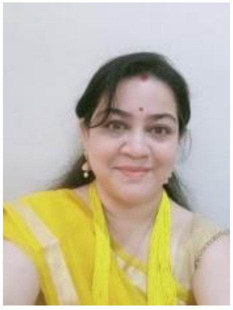

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