HYBRID CLASSIFIER FOR EPILEPTIC SEIZURES IN EEG SIGNALS USING TIME-DOMAIN FEATURES AND MACHINE LEARNING TECHNIQUES

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Abstract

This research investigates the common techniques with provides the detailed information on the epileptic seizure image database used along with the method applied for epilepsy image pre-processing. This also describes the proposed methodology implemented with hybrid method of the for epileptic seizures in EEG Signals using time-domain features and machine learning techniques. The proposed categories the Proposed research work retrieve the optimal features from EEG data and discussed the classifications of seizures and epilepsy which highly impact to the current researchers, patients and physicians is explored. Approximate entropy (ApEn) values of the wavelet coefficients applied to analysing the EEG signals within the ranges of time-series bands. Classification results were compared with three different machine learning methods applied on the same EEG dataset. It categorizes the Epileptic seizure and

performance can be evaluated from the datasets.

Keywords: CNNs, Epileptic Seizure Classification, Accuracy, Performance Metrics.

1 INTRODUCTION

Initially, the EEG Signal data downloaded from University of Bonn EEG signal datasets. The EEG data were captured from Healthy and Epileptic Seizure Persons. Usually EEG signals recorded by electrodes that are kept in human skull surface with time period of 23.6 secs with frequency rate of 173.6 Hz. This research work uses the standard data sets from this University of Bonn EEG signals has been used to test the applications. Totally, 4050 sample EEG data are taken into consideration of this research work. Among this 70% of sample EEG data used to train the algorithm and remaining 30% sample EEG data test the applications.

Over the past decade, the classification of epileptic seizures in EEG Signals has been a great challenge in computational methodology. The significant of this work in the flow of present status and according to World Health Organization (WHO) estimation report (2020) epilepsy is a human brain malfunction problem that exert influence on approximately 2% of the world's total population. Epileptic seizure is the powerful disorder of human brain, which is usually derived from Electroencephalogram (EEG) data. An epilepsy seizure usually obtained by unexpected and excessive activity disturbance neurons in the brain. The three different classifier algorithms used and compared the proposed algorithm in terms of metrics such as accuracy, sensitivity and specificity. The proposed method shows the classification accuracy of 95.5% from NN, that is considered to be in University of Bonn. CNNs are used wide applications like detection of objects, recognition or faces, feature extraction in image processing techniques etc. CNN is a deep learning network model which serves a main role in the process of performing recognition of features and classification of epileptic seizures. CNN basically takes parameters as inputs, and sends to feature learning process. The feature learning process consists of convolution layer and pooling layer of the network model. Convolution is the initial layer to extract features from an input layer. It is a mathematical function that takes two inputs namely, input matrix and a kernel or a filter. Pooling layer is a section of feature extraction, where the number of parameters of the input layer is reduced when it is found to be too large. Spatial pooling reduces the dimensionality of the input layer map, at the same time, it retains the essential information.

The main advantages of CNN based feature extraction are given as follows:

(i) Versatility of feature extraction method is found to be high and so it can be employed for linear as well as non-linear transformations including hard thresholding, scaling etc.

(ii) CNN employs parallel computing and so the processing speed is very high.

(iii) Replacement of handcrafted filters for machine learning is not necessary for CNN type of feature extraction tool.

2 PROPOSED METHODOLOGY

In current research, there has been a big effort made for the designing of the efficient technique for recognizing the epileptic seizure. This shows the need of three different procedures for recognition. These procedures proceed to have the diversified modules below

Pre-processing - This pre-processing module includes the identifying the outliers clustering techniques are used, similar values are clustered into a region or single cluster and the values that are external to the cluster-set are computed as outliers. Learning concepts usually keep on changing according to the learner's role. A differentiation amidst "active" and "passive" learners is established. Learner, who is active, interacts and coordinates with the environment during training time, either by asking queries or carrying out experiments, On the other hand, a passive learner merely views the information presented by the environment (or the teacher) without manipulating or affecting it. Usually, the learner of a spam filter tends to be passive – waiting for users to indicate incoming e-mails. Within active setting, the users could be requested for labeling particular e-mails selected or composed by the learner, to improvise the comprehension of spam.

Feature extraction - This module has the involvement of three image sets (finger, palm and knuckle print images). The Time Domain Features is used for extracting the needed features in this module.

- **Recognition** - This module deals with the non-recognition and recognition of the images. Learning can be considered as a broad-spread province. As a result, the machine learning techniques have spread across various sub-sectors handling diversified learning tasks. A tentative taxonomy of learning theories is presented for providing a perception so as to determine the right place of the content concerning the expanded province of machine learning. In order to classify learning models four models are presented. Supervised vs Unsupervised as learning comprises of interaction amidst the learner and the environment. The learning tasks can be split based on the class of interaction. First difference is the dissimilarity between supervised and unsupervised learning. To give an example, take into account the learning task of detecting spam e-mail vs. / anomaly detection task. For performing spam detection, there is a setting wherein the learner gets training e-mails for which the label spam/not-spam is given. Based on this training the learner must be able to decide a rule in order to label out a newly arrived e-mail message. In comparison the anomaly detection task is the one wherein the learners receive huge body of unlabeled e-mail messages as a training and the task of the learner involves identifying "unusual" or unknown messages. According to halfway learning strategy, the training instances involve much more information compared to the test examples/instances, the learner must anticipate additional information related to the test examples. For instance, a person might attempt to learn a value function, describing every setting of a chess-board and the scale by which White's place is superior to the Black's one. Still the learner can acquire only that position's information at the training time which actually takes place during the chess games, labeled by the winner of the game. These learning approaches are assessed under the heading of reinforcement learning.

Table 1. GLCM Descriptor with its significance

Time-domain Descriptor	**Significance**
Energy	Measuring the homogeneity or uniformity. Also called as second angular moment
Entropy	Measuring degree of randomness
Cluster Shade	Image's symmetrical lacking

Homogeneity	Measuring the uniformity in the image
Maximal Probability	Explores the emerging of the Gray value G1 of M which is adjacent to the Gray value G2 of N, by image domination

1.1 COMPONENTS OF RECOGNITION

The classification of epileptic seizure is considered as the importance factor in the research area due to the necessity for disease identification techniques. Hence, EEG signals captured that can be used to identify the nature of the abnormalities affecting the human brain. EEG signal Feature Extraction and classification is a crucial challenge in diagnosing, planning and treating Epileptic Seizure. This research work focuses on the development of an automatic computational methodology system, for the purpose of detecting anatomical and pathological features in EEG Signals, with its application to diagnosis of Epileptic Seizures related neurological disorders. To perform the proposed research work to classify the epileptic seizure the standard dataset used obtained from University of Bonn.The Figure 1. Illustrate the Overall Summarized Methodology of Research Workflow. Figure 2 Illustrate the Non-Epileptic Seizure EEG. Figure 3. Represents the Epileptic Seizure EEG.

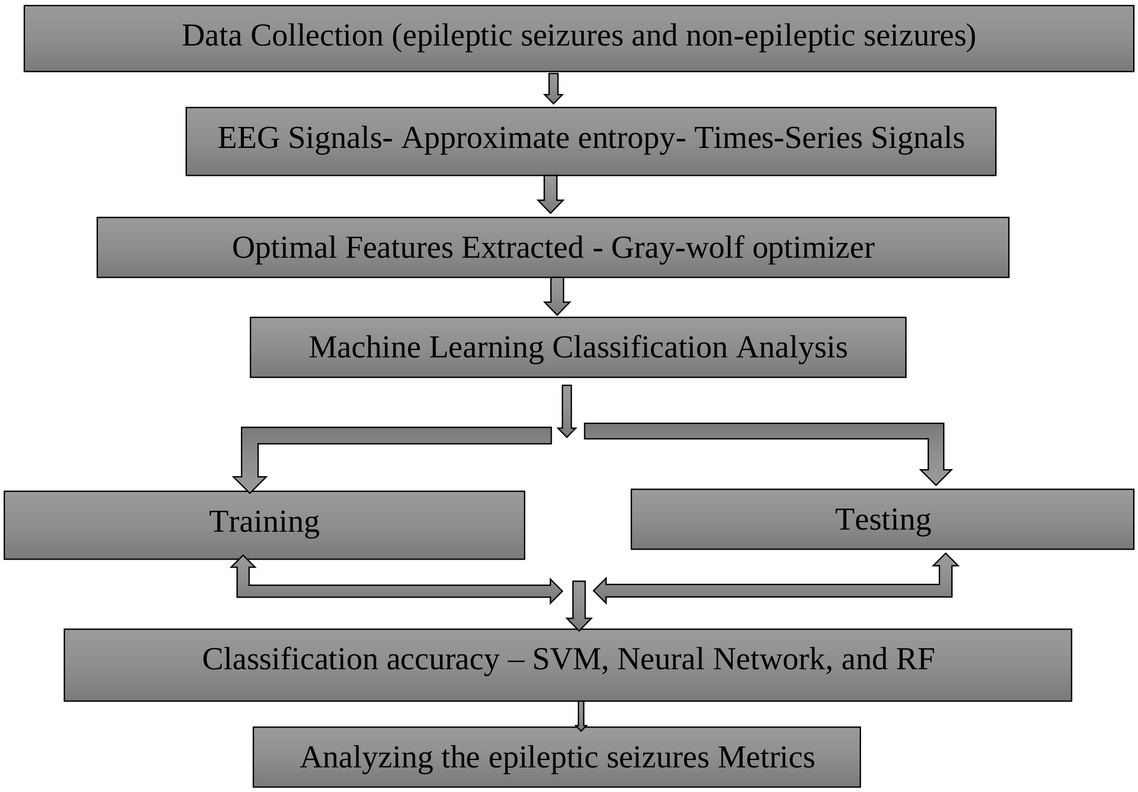


Figure 1. Overall Summarized Methodology of Research Workflow

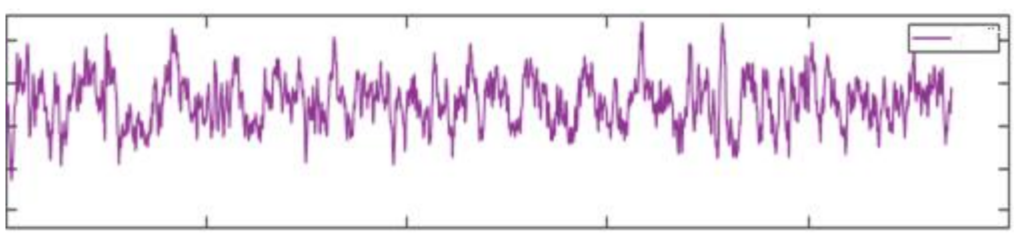


Figure 2. Non-Epileptic Seizure EEG

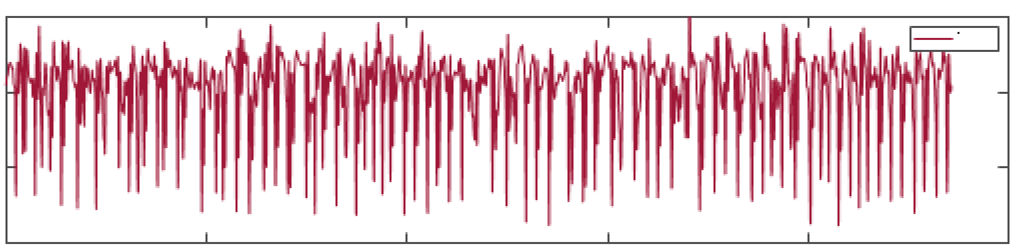


Figure 3. Epileptic Seizure EEG

Once EEG data are captures next step is extracted the parameters by applying Approximate Entropy techniques. Though we have the retrieve the relevant features from database. This Approximate Entropy automatically derives the time delay both Epileptic and non-epileptic EEG similarity data. This Approximate entropy techniques similarities values of the wavelet coefficients applied to analysing the EEG signals within the ranges of time-series bands. With the Gray-wolf optimizer used to selection of optimal features i.e., Approximate Entropy in EEG data. The usage of Optimization algorithm research work for selecting the best and optimal feature is very low. The EEG Signals features are obtained by optimization algorithm in order to optimize the best feature to attain the best accuracy, this investigates the current research work can serve as an economic alternate solution for Epileptic seizure.

Classification results were compared with three different machine learning methods applied on the same EEG dataset. The machine learning classification algorithms have been used it categorizes the Epileptic seizure and performance can be evaluated from the datasets. Table 2 and 3. Represents the Time and Frequency Domain Features extracted with its corresponding mathematical representation

Table 2. Time Domain Features extracted with its corresponding mathematical representation

S.No.	Time Domain Features	Mathematical Representation
1	Energy	$ENR = \sum_{i,j=0}^{N-1} -\log(G_{ij})^2$
2	Entropy	$ENT = \sum_{i,j=0}^{N-1} -\log(G_{ij})\,G_{ij}$
3	Sum entropy	$SE = -\sum_{i=0}^{2N-2} G_{x+y}(i)\log(G_{x+y}(i))$
4	Difference Entropy	$DE = -\sum_{i=0}^{N-1} G_{x+y}(i)\log(G_{x+y}(i))$
5	Singular Value Decomposition Entropy	$SSVDE = -\sum_{i} \delta_\iota \log \delta_\iota$
6	Distribution Entropy	$DEN(Y,n,A) = \frac{1}{\log A}\sum_{j=1}^{A} p_i \log p_i$
7	Fuzzy Entropy	$\varphi^m(r) = \frac{1}{(M-n)(M-n-1)} \sum_{i=0,i\neq 1}^{M-n} \sum_{i=0,}^{M-n} e^{\{d_{i,j}^2 \mid 2r^2\}}$
8	Permutation Entropy	$PE = \frac{1}{M-n-1}\sum_{i=0}^{M-n} f(s[i], \pi_k$
9	Sample Entropy	$\mathrm{SE} = \sum_{i=0,i\neq 1}^{M-n} \sum_{j=0}^{M-n} \Theta\,(k - \lVert\mu(i) - \mu(j)\rVert_\infty)$
10	Approximate Entropy	$(AP(EN)) = \frac{1}{M-n+1}\sum_{j=0}^{M-n} \Theta\,(k - \lVert\mu(i) - \mu(j)\rVert_\infty)$
11	Shannon Entropy	$SHE = -\sum_{j} G_j \log G_j$
12	Weighted Permutation Entropy	$WPE = \left(\sum_{k=1}^{n!} f(\pi_k)\log f(\pi_k)\right)$

13	Curve Length	$CL = \sum_{J=1}^{M-1} \lvert y[j] - y[j-1] \rvert$
14	Non-Linear Energy	$NLE = \sum_{j=1}^{M-2} (y^2[j] - y[J+1]y[j-1])$
15	Signal Complexity of Fractal Dimension Measurement	$SCFD = \lim_{e \to 0} \frac{\log M(e)}{\log 1/e}$

Table 3. Frequency Domain Features extracted with its corresponding mathematical representation

S.No.	Frequency Domain Features	Mathematical Representation
1	Energy	$ENR = \sum_{i,j=0}^{N-1} -\log(G_{ij})^2$
2	Mean Weighted Intensity Frequency	$MWIF(Y) = \sum_{j} y[j]f[j]$
3	Bandwidth of Intensity Weight	$BIW(Y) = \sqrt{\sum_{j} y[j]f[j] - MWIF[Y]^2}$
4	Spectral Entropy	$SE = \sum_{j} y[j] \log y[j]$
5	Frequency Spectral Edge	$\sum_{j=0}^{j_{FSE}} y[j] = 0.01 \propto$

3. RESULTS & DISCUSSION

Fig.4 illustrate the CNN Architecture. Fig. 5. Illustrate the Performance of CNN Analysis. Fig. 6. Illustrate the Training State CNN Analysis. Fig. 7. Illustrate the CNN Regression State Results.

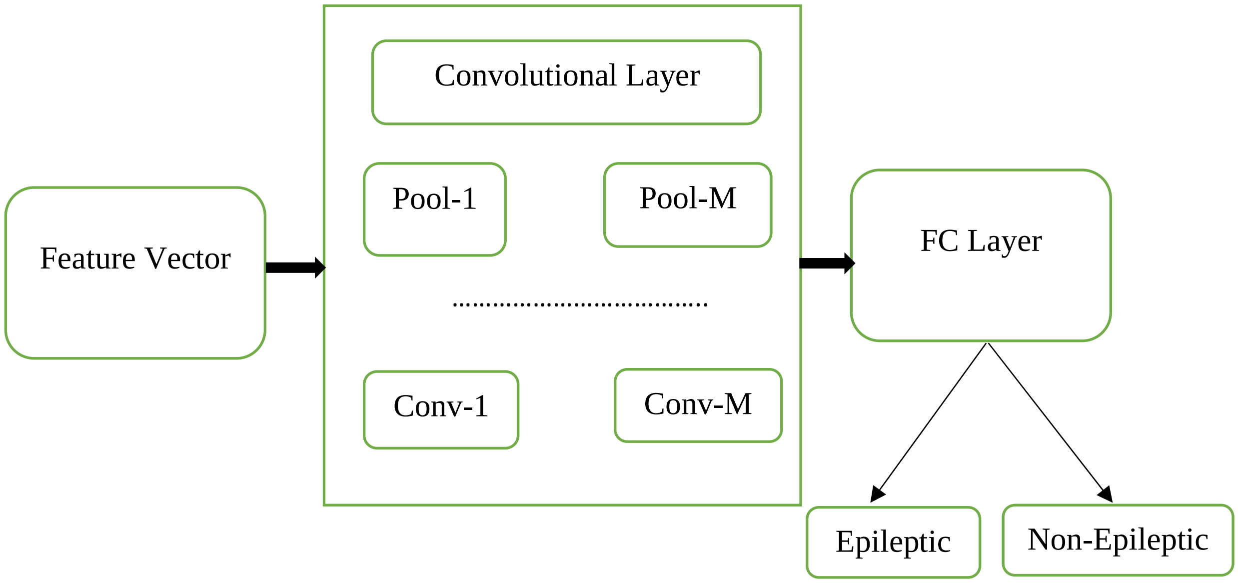
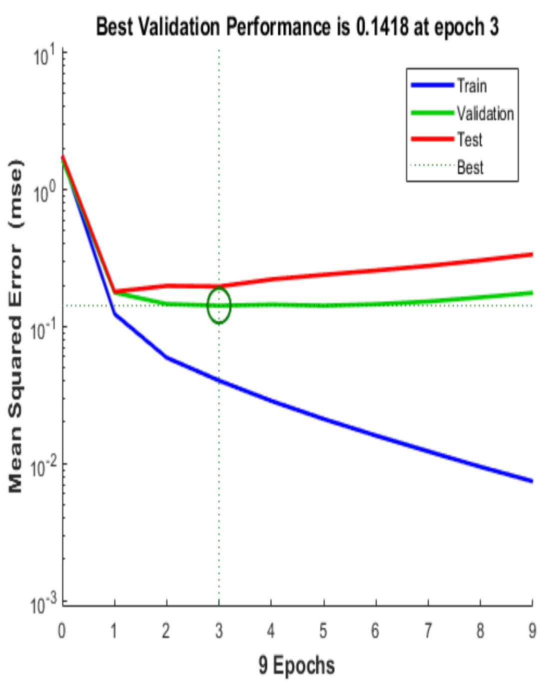


Fig.4 CNN Architecture



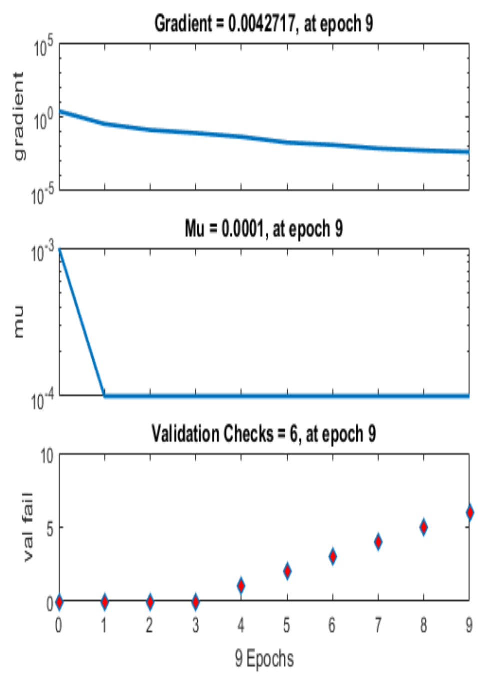


Fig. 5. Performance of CNN Analysis

Fig. 6. Training State CNN Analysis

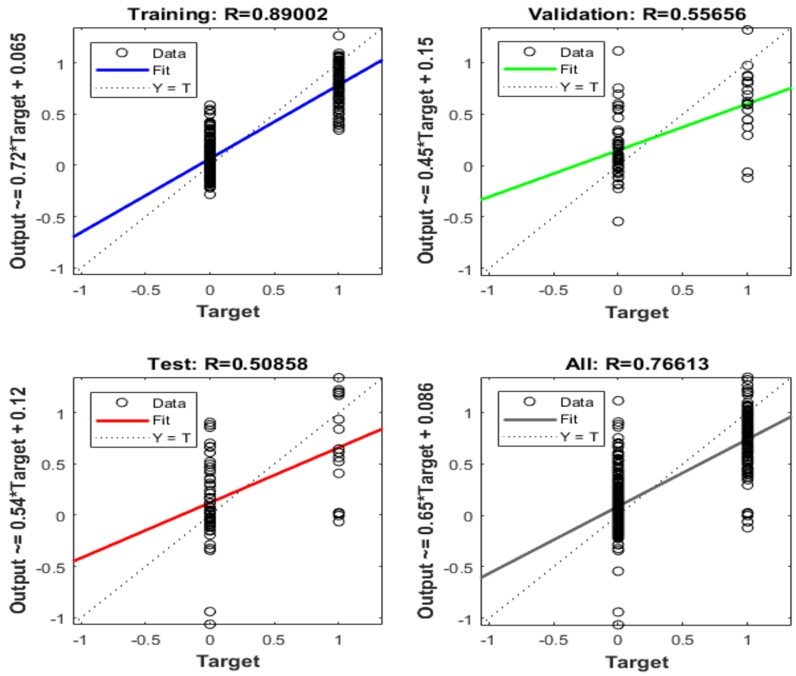
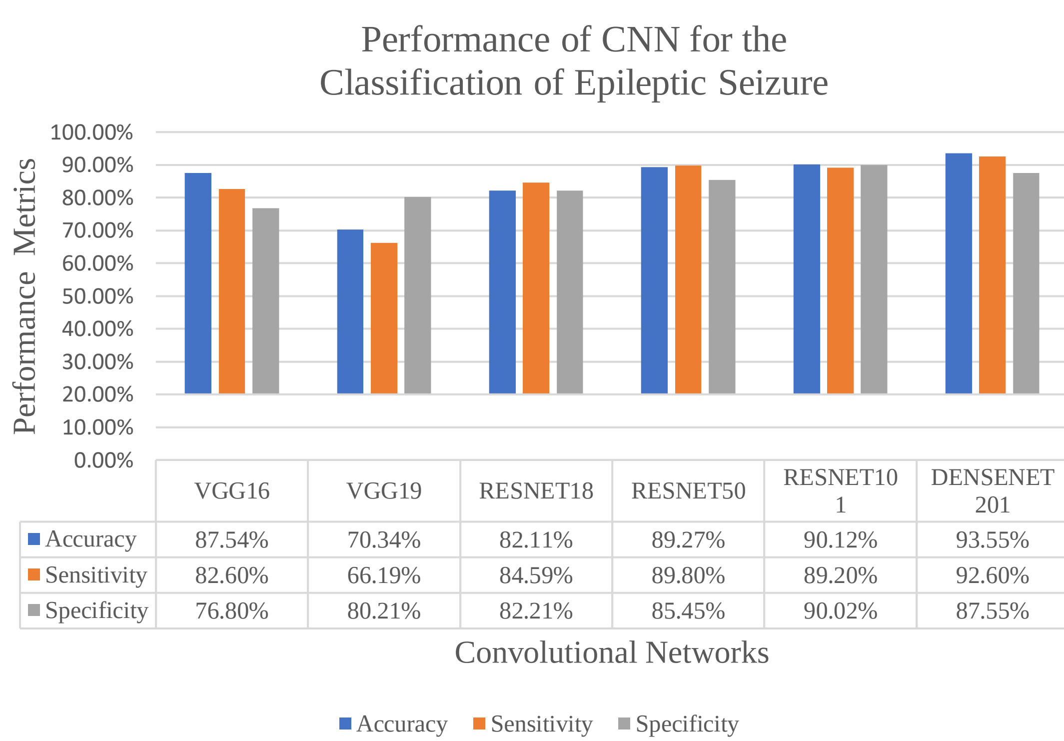


Fig. 7. CNN Regression State Results



	VGG16	VGG19	RESNET18	RESNET50	RESNET101	DENSENET 201
Accuracy	87.54%	70.34%	82.11%	89.27%	90.12%	93.55%
Sensitivity	82.60%	66.19%	84.59%	89.80%	89.20%	92.60%
Specificity	76.80%	80.21%	82.21%	85.45%	90.02%	87.55%

Fig.8. Performance of CNN for the Classification of Epileptic Seizure

From this Fig. 8, it is evident that DENSENET outperforms other networks in classifying the epileptic seizure with an accuracy of 93.55% as it considers concatenation of feature mapping instead of summation.

4. CONCLUSION

This can be easily accessible, have no side-effects, cost-effective and might also decrease the risk of epileptic seizure. The main advantages of CNN based feature extraction are given as follows: (i) Versatility of feature extraction method is found to be high and so it can be employed for linear as well as non-linear transformations including hard thresholding, scaling etc. (ii) CNN employs parallel computing and so the processing speed is very high. (iii) Replacement of handcrafted filters for machine learning is not necessary for CNN type of feature extraction tool.

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