Advanced Convolutional Neural Network Classification for Automatic Seizure Epilepsy Detection in EEG Signal

Venkata Ramana Mancha¹, Srinivasa Reddy E², Satyanarayana Ch³

¹Assistant Professor, Gitam University, Visakhapatnam, A.P., India
²Professor, Nagarjuna University, Guntur, A.P., India
³Professor, JNTUK University, Kakinada, A.P., India

Abstract

Epilepsy is one of the irregular electro-physiological disorder appeared in human brain, which is characterized by tonic recurrent seizures, Electroencephalogram (EEG) is a sufficient test measure to maintain records with respects to electrical activity of brain and it is widely used in analysis and detection of electro epileptic seizures. Manual inspection of EEG signal extraction will take more time to process and it puts heavy complex on neurologists affects their performance. It is often difficult in identification of brain subtle but emergency changes in EEG wave forms by visual inspection based on research area for bio- engineers implement different types of methodologies for identification of such type of subtle. But all these algorithms/ methodologies don’t perform efficient accuracy in classification of normal, ictal class instances. So that in this paper, we propose a novel system based on machine learning, which is single dimensional pyramidal ensemble convolutional neural network (1D-PECNN). Here ensemble means different parts of the signal are assigned to different models for efficient analysis of data. We also propose mathematical augmented approach for learning features. In 1D-PECNN model, system consist high amount of desirable and learnable parameters, in all cases proposed approach 1D-PECNN gives maximum accuracy (Approximately from 92%-99%) when compare to state-of-the methods.

Index Terms: Epilepsy, convolutional neural networks, visual inspection, electroencephalogram, epileptic seizures, non-linear analysis and feature extraction.

I. Introduction

Peoples who experienced seizure may influence epilepsy. Epilepsy is the average condition influencing around 65 million individuals worldwide.[1] According to the ongoing review about 2.3 million Americans were influenced by epilepsy. The general population who experienced seizure may loses their cognizant for quite a while causing modification in conduct and sensation. Epilepsy individual may have increasingly number of seizure types. Epileptic seizure has two sorts in particular incomplete (central) and summed up. The side effects for seizure were periodic blacking out spells and biting or flickering at unseemly time. The triggers for seizure are parchedness, photosensitivity, absence of rest, stress, and so forth. PNES, is the sort of non-epileptic seizure which is generally called pseudo seizures, are a moderately phenomenal confusion with a predominance of around 1 to 33 cases for every 100 000 and they represent 5–20% of patients thought to have epilepsy [3]. There is potential for serious damage from the unfavorable reactions or teratogenicity of antiepileptic drugs endorsed to PNES patients [4], just as horribleness and mortality from intubation for delayed seizures [5].For recognizing and investigating epileptic seizure, EEG has set up. Electroencephalogram is the procedure in which seizure can be analyzed. The cathodes are utilized for acquiring the electrical signs from the human mind. EEG signals are commonly spoken to in high dimensional component space. It is hard to decipher EEG signals. For deciphering and breaking down high dimensional list of capabilities AI techniques are utilized. Specialists have proposed techniques for the recognition of seizures utilizing highlights separated from EEG motions by hand-designed systems.

A portion of the proposed techniques utilize ghastly (Tzallas et al., 2012) and worldly parts of data from EEG signals (Shoeb, 2009). An EEG flag contains lowfrequency highlights with long timeframe and high-recurrence...
highlights with brief timespan (Adeli et al., 2003) for example there is a sort of chain of command among highlights. Profound learning (DL) is a cutting edge ML approach which naturally encodes pecking order of highlights, which are not information subordinate and are adjusted to the information; it has indicated promising outcomes in my applications. Also, highlights extricated utilizing the DL models have appeared to be more discriminative and vigorous than hand-structured highlights (LeCun et al., 1995). So as to improve the exactness in the arrangement of epileptic and non-epileptic EEG signals, we propose a strategy dependent on DL.

We propose a novel system based on machine learning, which is single dimensional pyramidal ensemble convolutional neural network (1D-PECNN). We also propose mathematical augmented approach for learning high amount of features. Our proposed approach takes signals of EEG and fixed them into single data window with different attributes and they pass those instances into associated PECNN model. It outperforms the state of the methods for various issues concerning epilepsy discovery. The principle commitments of this investigation are: 1) information enlargement plans, 2) a framework dependent on a gathering of P-1D-CNN profound models for parallel just as ternary EEG flag grouping, 3) another methodology for organizing profound 1D-CNN model and 4) exhaustive assessment of the expansion plans and the profound models for identifying distinctive epilepsy cases.

II. BACKGROUND RELATED WORK

We present a concise audit of seizure-related wording, the seizure recognition writing, and the one-class SVM.

2.1. Seizure-Related Terminology

Seizure investigation alludes all things considered to calculations for seizure recognition, seizure expectation, and programmed center channel recognizable proof. These investigations are principally performed on the EEG. In this investigation, examinations were completed on the intracranial EEG (IEEG), which has significantly better spatial goals, higher flag to-clamor proportion, and more noteworthy transfer speed than scalp EEG. At the point when various channels are considered, the anode area that shows the most punctual proof of seizure movement is named the center channel. It is advantageous to depict sections of the EEG motions by their worldly nearness to seizure movement. The ictal period alludes to the time amid which a seizure happens. The interictal period is the time between progressive seizures. The unequivocal electrographic beginning (UEO) is characterized as the most punctual time that a seizure event is obvious to an epileptologist seeing an EEG without earlier information that a seizure pursues; the unequivocal clinical beginning (UCO) is the most punctual time that a seizure event is obvious by outwardly watching a patient. Seizure beginning in this paper is synonymous with UEO. It is significant that the UEO quite often goes before the UCO by a few seconds, and that numerous recently distributed papers characterized "seizure beginning" as the UCO.

2.2. Seizure Detection

Early endeavors to distinguish seizures started during the 1970s (Viglione, Ordon and Risch, 1970; Liss, 1973) and principally considered scalp EEG chronicles to identify the clinical (and less as often as possible) electrographic beginning of seizures. In 1990, Gotman revealed a strategy for mechanized seizure identification that accomplished 76% location precision at 1 Fp/hr for 293 seizures recorded from 49 patients (Gotman, 1990). In 1993, it was demonstrated that the brief timeframe mean Teager vitality could be utilized to identify seizures from electrocorticograms (Zaveri, Williams and Sackellares, 1993). Their identifier accomplished 100% recognition exactness on a 11-seizure database. In 1995, Qu and Gotman displayed an early seizure cautioning framework prepared on format EEG action that accomplished 100% location exactness at a mean recognition inertness of 9.35 seconds and false alert rate of 0.2 Fp/hr (Qu and Gotman, 1995). Comparative outcomes were additionally announced utilizing time-and recurrence area highlights grouped by a k-closest neighbor classifier (Qu and Gotman, 1997). In 1998, Osorio et al. guaranteed 100% identification affectability with a mean recognition idleness of 2.1 seconds utilizing a wavelet based measure called seizure power. They broke down a database of 125 patients, yet
similar information were utilized for preparing and approval (Osorio, Frei and Wilkinson, 1998). The calculation was all the more widely dissected in 2002 utilizing disconnected electrocorticogram chronicles; once more, 100% affectability was accounted for, with identification latencies extending from 1.8 – 31.1 seconds (Osorio et al., 2002).

A few effective endeavors at seizure discovery utilizing fake neural system classifiers have been accounted for since 1996 (Khorasani and Weng, 1996; Webber et al., 1996; Gabor, 1998; Esteller, 2000). Assessment of 31 particular highlights (Esteller, 2000) demonstrated that fractal measurement, wavelet parcel vitality, and mean Teager vitality were particularly encouraging for seizure recognition. In 2001, Estelle announced an identifier dependent on the line length include that accomplished a mean discovery inertness of 4.1 seconds at a bogus caution rate of 0.051 Fp/hr (Esteller et al., 2001). An aggregate of 111 seizures (numerous subclinical) were utilized for approval. NeuroPace, Inc., in this manner announced a comparative locator dependent on this work accomplished 97% affectability at a mean discovery idleness of 5.01 seconds (Echauz et al., 2001). This finder was assessed on 1265 hours of IEEG information, yet was tuned heuristically in a patient-explicit way. The NeuroPace finder claims speak to the best in class in seizure recognition execution. Progressively total surveys of the seizure identification and forecast writing are accessible somewhere else (Litt and Echauz, 2002; Gardner, 2004).

III. PROPOSED IMPLEMENTATION

In this section, we describe the procedure of single dimensional pyramidal ensemble convolutional neural network (1D-PECNN). We describe the procedure of deep learning convolutional neural networks to train epileptic eye related data for feature extraction and the identify the relevant data relates to epileptic data.

Deep Convolutional Neural Networks: In this work, sequential procedure of the convolution neural networks on EEG data related to human. A point by point representation of the proposed recovery framework is appeared in Fig. 1. The hidden DCNN model intends to learn channel part by creating an increasingly unique portrayal of the information in each layer.

![Figure 1 Proposed architecture implementation using convolutional neural networks.](image_url)

In spite of its straightforward arithmetic, DCNN is as of now the most amazing asset in vision frameworks. The DCNN models by and large have three sorts of layers i.e., convolutional layers, pooling layers, and completely associated layers. The yield layer is commonly treated independently as a special layer and the model gets information tests at the information layer. Each convolutional layer produces highlight maps by convolving the part with information highlight maps. A pooling layer is intended to down example highlight maps created by the convolutional layers, which is frequently practiced by discovering nearby maxima in a neighborhood. Additionally, pooling gives translational invariance and in the then it lessens the quantity of neurons to be prepared in up and coming layers. In completely associated layers, every neuron has an increasingly denser association when contrasted
with the convolutional layers. The piece of the DCNN before completely associated layers is known as feature extractor part and after that is known as classifier part. A de-followed portrayal of the structure utilized is exhibited in following subsections.

The model utilized for preparing comprised of eight layers, out of which five are convolutional layers and three are completely associated layers, as delineated in Fig. 2. The convolutional and completely connected layers are spoken to as CVL and FCL, where the subscript speaks to the layer number e.g., CVL 1 speaks to the first convolutional layer. The yield of last completely associated layer (FCL 3 ) has been bolstered to a soft-max capacity having 24 yields, which produce likelihood dispersions for each class mark. Subsequently, the probabilities vector of size 1 ×24 where every vector component relates to a class of dataset is gotten. The system acknowledges grayscale image-periods of measurement 224 ×224 as sources of info and not at all like the model presented in [11] utilize a lesser number of bits. The CVL 1 channels the info picture with 64 portions of size 11 ×11 with walk equivalent to 4 pixels. The walk is the separation between the focuses of open fields of neighborhood neurons in the portion map. The yield of the first convolutional layer is encouraged to a non-linearity and after that went through the spatial max pooling layer for abridging neighboring neurons. Redressed straight unit (ReLU) [26] nonlinearity is ap-utilized to the yields of all convolutional and completely associated layers. This system with ReLUs has not just the capacity to get prepared a few times quicker than its proportional with tanh units [27] however it likewise permits to go further with evaporating angle issues.

The CVL 2 takes the yield of CVL 1 as information prepared by ReLU non-linearity and spatial max-pooling layers separately and channels it with 192 bits of size 5 ×5. The CVL 3 contains 384 parts of size 5 ×5 and it gets a contribution from the pooled yields of the second convolutional layers. Both the convolutional layers, CVL 4 and CVL 5 have 256 pieces of size 3 ×3. All completely associated layers have an equivalent number of neurons i.e., 4096.

**Training Image Sequences:**

Stochastic Gradient Descent (SGD) is commonly used calculation for preparing neural systems and it is productive learning with description straight under classifier a raised misfortune capacity like support vector machine (SVM). The two noteworthy favourable circumstances of utilizing SGD are effectiveness and straightforwardness in execution giving choices in tuning the system like various cycles, processing rate, rate rot, and so forth. A couple of inconveniences of SGD incorporate its requirement for hyper-parameters like various ages or emphasis optimized and regularized parameters. SGD update each parameter preparation test xi and mark yj. Eq. (1) is utilized for parameter update of the SGD

\[ \theta = \theta - \eta \Delta \phi J(\theta, x', y') \]
J be the objective function, will optimize the relations based on weights of each pixel.

Figure 3.5 Description of different layers with different parameter sequences in training phase.

When the convolution model is effectively upgraded and prepared for grouping the medicinal pictures, pixel representations are extricated from last pixel to pixel formation in completer associated layer in pre-processing model i.e., from FCL 1 FCL 3. For picture recovery task a locally settled highlights image data source for the entire preparing information is required. In this way, to make such highlights database, each picture $x_I$ from preparing set is feed sent to the prepared DCNN model for arrangement undertaking and afterward includes portrayal $F_{1I}$, $F_{2I}$, and $F_{3I}$ are extricated related to that particular picture from completely associated layers 1 3, individually. The $F_{1I}$, speaks to a highlights database separated from FCL 1 and likewise $F_{2I}$ and $F_{3I}$ speaks to highlights databases removed from FCL 2 and FCL 3, where $I = 1$ to $P$ and $P$ is equivalent to number of tests in preparing set. At whatever point an inquiry is defined, comparative pictures as that of question picture are recovered by looking at highlight portrayals extricated for inquiry picture features are representation using in Euclidean distance described as follows:

$$d(a, b) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}$$

As described in above, a, b, are the initial image data partitions separately which is shown in figure 3.5, and also describe the disseminating the pixel calculation of image from image data sources. Pictures have high image intensity or high similitude when contrasted with others is shown as recovery results to the client. At last, relative examination is performed for features portrayals separated from FCL 1, FCL 2, FCL 3 and convolution layer as far as recovery quality
3.1. Procedure to Explore Epilepsy in Convolutional Layers

Describe the procedure used in detection of epilepsy in human eye related EEG data sets.

**Algorithm 1** Step by step procedure to explore different statistical data evaluation in CNN.

Description for accessing relevant data from epileptic data, calculate the kernel parameter functionalities to describe connected layer communication in epileptic data evaluation.

3.2. Layers in Convolution

Convolutional layers operation in one-dimensional used to filter EEG signals to extract features. Convolution layer is generated by convoluting existing layers with respect to respective field (rf) and depth and is equivalent to number of features present in existing layer. Formally convoluting layer $A = \{a_{ij} : 1 \leq i \leq n, 1 \leq j \leq m\}$, where $n$ is no. of channel in layer and $m$ is the no. of units in channel with $k^{th}$ kernel $k, l = 1, 2, \ldots, K$ each of the respective field and depth $n$ convolutional layer $B = \{b_{ij} : 1 \leq i \leq q, 1 \leq j \leq K\}$ where

$$a_{ij} = \sum_{d=1}^{q} \sum_{e=1}^{k} w_{de} x_{i+d,j+e}$$

$m$ is no. of units in each channel of layer, convolutional layer, number of channels are integrated with no. of kernel specifications to extract discriminative features from input data as shown in figure 2. In proposed model, for each convolutional layer, it reduces pyramid structure based on no. of kernels in detection epilepsy.

IV. Performance Evaluation

We laid it on the line the explain of announcement, and the eventual story augmentation schemes. Then, we try evaluation measures, which have been secondhand to do justice to the stunt of the approaching system. After this, the training procedure has been elaborated. Finally, the of the first water data augmentation step by step diagram and
P-1D-CNN person to look up to have been latent by analyzing the results with diverse ways of data augmentation, and diverse 1D-CNN models.

4.1. Dataset Description

The informational collection utilized in this work was gained by an examination group at University of Bonn (Andrzejak et al., 2001) and have been broadly utilized for research on epilepsy identification. The EEG signals were recorded utilizing standard 10-20 terminal arrangement framework. The total information comprises of five sets (A to E), each containing 100 one-channel occurrences. Sets An and B comprises of EEG signals recorded from five solid volunteers while they were in a loose and wakeful state with eyes opened (An) and eyes shut (B), separately. Sets C, D, and E were recorded from five patients. EEG motions in set D were taken from the epileptogenic zone. Set C was recorded from the hippocampus arrangement of inverse side of the equator of the cerebrum. Sets C and D comprise of EEG signals estimated amid sans seizure interims (interictal), while, the EEG motions in Set E were recorded just amid seizure action (ictal) (Andrzejak et al., 2001). The detail is given in Table 1.

| A         | B         | C     | D     | E     |
|-----------|-----------|-------|-------|-------|
| Non-Epileptic | Non-Epileptic | Epileptic | Epileptic | Epileptic |
| Eyes opened | Eyes closed | Interictal | Interictal | Ictal |

Table 1 Data sets used for different attributes.

The number of instances collected in this dataset is not enough to train a deep model. Acquiring a large number of EEG signals for this problem is not practical and their labeling by expert neurologists is not an easy task. We need an augmentation scheme that can help us in increasing the amount of the data that is enough for training deep CNN model, which requires large training data for better generalization.

4.2. Performance Metrics

For assessment, we received 10-overlap cross approval for guaranteeing that the framework is tried over various varieties of information. The 100 signs for each class isolated into 10 overlap, each crease (10%), thusly, is kept for testing while the rest of the 9 folds (90% signs) are utilized for learning the model. The normal execution is determined for 10 folds. The execution was assessed utilizing understood execution measurements, for example, exactness, explicitness, affectability, accuracy, f-measure, and g-mean. A large portion of the cutting edge frameworks for epilepsy additionally utilize these measurements, the adjustment of these measurements for assessing our framework helps in reasonable examination with best in class frameworks. The meanings of these measurements are given underneath.

\[
Accuracy(Acc) = \frac{TP + TN}{Total - Samples}
\]

\[
Specificity(Spe) = \frac{TN}{TN + TP}
\]

\[
Sensitivity(Sen) = \frac{TP}{FN + TP}
\]

\[
F\text{-measure}(F\text{ }_m) = \frac{2 \times \text{precision} \times \text{sensitivity}}{\text{precision} + \text{sensitivity}}
\]

\[
G\text{-Mean}(G\text{ }_m) = \sqrt{\text{Specificity} \times \text{Sensitivity}}
\]
where TP (true positives) is the quantity of strange cases (for example epileptic), which are anticipated as anomalous, FN (false negatives) is the quantity of strange cases, which are anticipated as should be expected, TN (genuine negatives) is the quantity of ordinary case that is anticipated as should be expected and FP (false positives) is the quantity of typical cases that are distinguished as anomalous by the framework.

4.3. Results

Table 2 shows our proposed accuracy values with respect to existing techniques with different value formats as follows:

Table 2. Different accuracy values with different attributes.

| Databases | Proposed Approach | Existing Previous [3] | Existing Previous [4] | Existing Previous [5] |
|-----------|-------------------|------------------------|------------------------|------------------------|
| Data Class 1 | 0.84 | 0.712 | 0.689 | 0.696 |
| Data Class 2 | 0.736 | 0.51 | 0.708 | 0.562 |
| Data Class 3 | 0.746 | 0.764 | 0.576 | 0.415 |
| Data Class 4 | 0.832 | 0.604 | 0.484 | 0.423 |
| Data Class 5 | 0.832 | 0.470 | 0.508 | 0.371 |

Figure 3 shows the accuracy presentation of proposed approach with different Elliptic Data databases.

Table 3 follows precision representative values with different Epilepsy Data’s in optimization of Epilepsy Data query retrieval.

Table 3. Different values with respect to precision.

| Epilepsy Data Achieves | Proposed Approach | Existing System [3] | Existing System [4] | Existing System [5] |
|------------------------|-------------------|---------------------|---------------------|---------------------|
| Epilepsy Data Class 1 | 0.56 | 0.342 | 0.4245 | 0.352 |
Table 4. Recall values with different Epilepsy Data databases.

| Databases            | Proposed Approach | Existing Previous [3] | Existing Previous [4] | Existing Previous [5] |
|----------------------|-------------------|------------------------|------------------------|------------------------|
| Epilepsy Data Archive 1 | 0.61              | 0.412                  | 0.501                  | 0.427                  |
| Epilepsy Data Archive 2 | 0.552             | 0.346                  | 0.496                  | 0.468                  |
| Epilepsy Data Archive 3 | 0.598             | 0.486                  | 0.346                  | 0.367                  |
| Epilepsy Data Archive 4 | 0.61              | 0.462                  | 0.454                  | 0.329                  |
| Epilepsy Data Archive 5 | 0.61              | 0.376                  | 0.396                  | 0.356                  |

Table 4 shows recall effective Epilepsy Data retrieval formation with relevant and irrelevant Epilepsy Data’s from different Epilepsy Data datasets.
Figure 5 shows effective Epilepsy Data retrieval formations with different query Epileptic Data’s from different Epilepsy Data datasets. In the all five different dataset recovery were done by querying five different pictures and for every dataset we get perfection, remember and F-measure principles is identified. The perfection and remember value evaluation between the suggested comprehensive methods functions removal centered on multi-objective marketing techniques demonstrates the efficiency of the suggested system is best over that of the current systems.

V. Conclusion

In this paper, a programmed framework for epilepsy identification has been proposed, which manages paired identification issues (epileptic versus non-epileptic or seizure versus non-seizure) and ternary recognition issue (ictal versus typical versus interracial). The proposed framework depends on profound realizing, which best is in class ML approach. The proposed framework gives extraordinary execution with less information and less parameters. It will help nervous system specialists in recognizing epilepsy, and will enormously decrease their weight and increment their proficiency. In practically every one of the cases concerning epilepsy recognition, the proposed framework gives an exactness of 99.1±0.9% on the University of Bonn dataset. The framework can be helpful for other comparative arrangement issues dependent on EEG mind signals. At present, the epilepsy discovery techniques recognize seizures after their event. In future, we will examine its convenience for identifying seizures preceding their event, which is a testing issue.

References

[1] Ihsan Ullah, Muhammad Hussain, Emad-ul-Haq Qazi, "An Automated System for Epilepsy Detection using EEG Brain Signalsbased on Deep Learning Approach", Paper presented at the Signal-Image Technology & Internet-Based Systems (SITIS), 2016.
[2] Acharya, U. R., Molinari, F., Sree, S. V., Chattopadhyay, S., Ng, K.-H., & Suri, J. S. (2012). Automated diagnosis of epileptic EEG using entropies. Bio Signal Processing and Control, 7(4), 401-408.
[3] Cui, Z., Chen, W., & Chen, Y. (2016). Multi-scale convolutional neural networks for time series classification. arXiv preprint arXiv:1603.06995.
[4] Ince, T., Kiranyaz, S., Eren, L., Askar, M., & Gabbouj, M. (2016). Real-time motor fault detection by 1-D convolutional neural networks. IEEE Transactions on Industrial Electronics, 63(11), 7067-7075.
[5] Ioffe, S., & Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. Paper presented at the International Conference on Machine Learning.
[6] Ji, S., Xu, W., Yang, M., & Yu, K. (2013). 3D convolutional neural networks for human action recognition. IEEE transactions on pattern analysis and machine intelligence, 35(1), 221-231.
[7] Kingma, D., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
[8] Koffler, D., & Gotman, J. (1985). Automatic detection of spike-and-wave bursts in ambulatory EEG recordings. Electroencephalography and clinical neurophysiology, 61(2), 165-180.
[9] Zhang, T., Chen, W., & Li, M. (2017). AR based quadratic feature extraction in the VMD domain for the automated seizure detection of EEG using random forest classifier. Bio Signal Processing and Control, 31, 550-559.

[10] Tran, D., Bourdev, L., Fergus, R., Torresani, L., & Paluri, M. (2015). Learning spatiotemporal features with 3d convolutional networks. Paper presented at the Proceedings of the IEEE international conference on computer vision.

[11] Saab, M.E. and Gotman, J. (2005) A system to detect the onset of epileptic seizures in scalp EEG. Clinical Neurophysiology, 116, 427-442. doi:10.1016/j.clinph.2004.08.004

[12] Indiradevi, K.P., Elias, E., Sathidevi, P.S., Dinesh, S. and Radhakrishnan, K. (2008) A multi-level wavelet approach for automatic detection of epileptic spikes in the electroencephalogram. Computers in Biology and Medicine, 38, 805-816. doi:10.1016/j.compbiomed.2008.04.010

[13] Übeyli, E.D. (2009) Automatic detection of electroencephalographic changes using adaptive neuro-fuzzy inference system employing Lyapunov exponents. Expert Systems with Applications, 36, 9031-9038. doi:10.1016/j.eswa.2008.12.019

[14] Ghosh-Dastidar, S., Adeli, H. and Dadmehr, N. (2007) Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection. IEEE Transactions on Bio Engineering, 54, 1545-1551. doi:10.1109/TBME.2007.891945

[15] Kannathal, N., Choo, M.L., Rajendra, A.U. and Sadasivan, P.K. (2005) Entropies for detection of epilepsy in EEG. Computer Method and Programs in Biomedicine, 80, 187-194. doi:10.1016/j.cmpb.2005.06.012

[16] Ocak, H. (2008) Optimal classification of epileptic seizures in EEG using wavelet analysis and genetic algorithm. Signal Processing, 88, 1858-1867. doi:10.1016/j.sigpro.2008.01.026

[17] Srinivasan, V., Eswaran, C. and Sriraam, N. (2007) Approximate entropy-based epileptic EEG detection using artificial neural networks. IEEE Transactions on Information Technology in Biomedicine, 11, 288-295.

[18] T.Rajesh kumar, K.Geetha, R.Satheesh, S.Barkath Nisha, MRI Brain Image Segmentation using Fuzzy C Means Cluster Algorithm for Tumor Area Measurement, International Journal of Engineering Technology Science and Research, ISSN 2394 – 3386, Volume 4, Issue 9.

[19] V. Srinivasan, C. Eswaran, and A. N. Sriraam, “Artificial neural network based epileptic detection using time-domain and frequency-domain features”, Journal of System, vol. 29, no. 6, (2005), pp.647–660.

[20] V. Srinivasan, C. Eswaran, and N. Sriraam, “Approximate entropy-based epileptic EEG detection using artificial neural networks,” Transactions on Information Technology in Biomedicine, vol. 11, no. 3, (2007), pp. 288–295.

[21] A. S. Zandi, G. a Dumont, M. Javidan, R. Tafreshi, B. a MacLeod, C. R. Ries, and E. Pui, “A novel wavelet-based index to detect epileptic seizures using scalp EEG signals”, Conf. Proc. Engineering in Medicine and Biology Society, vol. 2008, no. 2, (2008), pp. 919–922.

[22] G. Chen, “Automatic EEG seizure detection using dual-tree complex wavelet-Fourier features”, Expert System Application, vol. 41, no. 5, (2014), pp. 2391–2394.

[23] A. Shoeb and J. Guttag, “Application of Machine Learning To Epileptic Seizure Detection”, Proceedings of the 27th International Conference on Machine Learning , (2010) pp. 975–982.

[24] P. Bhatia and A. Sharma, “Different Techniques for Extracting Brain Signals for Human Machine Interface , a Review”, Australian Journal of Information Technology and Communication, vol. 2, no. 2, (2015), pp. 31–34.

[25] S. Garg and R. Narvey, “Denoising and Feature Extraction of EEG Signal Using Wavelet Transform”, International Journal of Engineering, Science & Technology, vol. 5, (2013), pp. 1249-1253.

[26] G. Kaushik, H. P. Sinha, and L. Dewan, “Bio Signals Analysis by Dwt Signal Denoising with Neural Networks”, vol. 3, no. 1, (2013), pp. 1–18.

[27] I. Omerhodzic, S. Avdakovic, A. Nukanovic, K. Dizdarevic, " Energy distribution of EEG signals: EEG signal wavelet-neural network classifier", arXiv preprint arXiv:1307.7897, 2013.