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DETECTION OF EPILEPTIC SEIZURES USING EEG SIGNALS

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ABSTRACT

According to the World Health Organization (WHO), epilepsy is a chronic neurological circumstance illustrated by an excessive and uncontrolled electrical explosion. It is a rare occurrence that affects people of various ages. An electroencephalogram (EEG) of brain activity is a well-known tool for studying epileptic convulsions and recording changes in electrical activity in the brain. Consequently, epilepsy prediction and early diagnosis are required to give timely preventative measures to free patients from the detrimental repercussions of epileptic seizures. Despite decades of research, accurately projecting these seizures remains an unsolved challenge. This paper proposed epilepsy seizure detection and classification using a deep learning model called CNN and LSTM. In the convolutional layer, numerous features are extracted from EEG signal files, while in the optimization layer, non-essential elements are eliminated. In an extensive experimental analysis, we validated the system with a real-time EEG dataset, where we obtained 82.5% accuracy for epilepsy detection for the entire testing dataset.

Keywords: *EEG Signals, Epilepsy Seizure Detection, Brain Computer Interaction, Feature Extraction, Classification, Deep Learning*

1. INTRODUCTION

An electroencephalogram (EEG), which captures the flow of electricity created as impulses are transferred between cranial nerves, is used to diagnose and investigate seizures. Depending on the region to be studied, EEG may be categorized into two types: cerebral EEG and scalp EEG. An invasive EEG records electrical signals of the prefrontal cortex by connecting electrodes directly to the cerebrum accessible during surgery. Scalp EEG uses electrodes attached to the scalp to measure EEG signals. Cerebrospinal fluid EEG can collect noise-free signals, but because the skull must be perforated, the scalp EEG measuring technique, utilized for regular monitoring patients and seizure alert generating, has greater applicability and convenience of use. Furthermore, the EEG condition of a seizure patient may be categorized into four groups based on the EEG record: It is first named the ictal at the commencement of a seizure. Second, the preictal state occurs before the commencement of seizures. Third, the interictal state occurs after the seizures have ended.

Seizures are unpredictable, and since it's impossible to anticipate when they'll happen, persons with epilepsy are restricted in their social events and are constantly in danger of injury. As a result, investigations on seizure prediction utilizing EEG signals have been ongoing to provide enough time to raise an alert and take necessary action before a seizure occurs. A discrepancy between the postictal and preictal periods is the first step in seizure prediction. It detects that prodromal interval and provides an alert before the seizure begins. Machine learning has been extensively employed in seizure prediction in recent years. However, contemporary research has mostly focused on deep learning models that exhibit outstanding performance in machine vision and voice recognition. Deep Neural Networks (CNN), commonly employed in image recognition and outstanding performance, have piqued researchers' interest in seizure prediction. The trained classifier predicts the presence of seizures by recognizing the prodromal interval in the fresh EEG data using the deep learning approach employing this CNN.

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The research paper is divided into the following sections. Section 1 comprises the introduction to the topic. Section 2 describes the related work of various researchers on detecting epileptic seizures using EEG signals employing multiple machine learning approaches and their gaps. Section 3 illustrates the proposed system architecture design. Algorithm design, results and discussions are described in Sections 4 and 5, respectively. Thus, Section 5 elaborates the detailed conclusion of our proposed system.

2. LITERATURE SURVEY

Shreya Gautam et al. [1] published a study in 2015 which said that the assessment of matching resulting maxima after procedures on Electroencephalogram (EEG) signals is used to design a new technique for classifying focal as well as non-focal epilepsy. The electroencephalogram (EEG) signal is decomposed using empirical mode decomposition (EMD) to produce intrinsic mode functions (IMFs) that are then independently performed to complete the analysis. Zayneb Brari et al. [2] proposed a novel approach for automated epilepsy identification using encephalographic data in 2020. In their investigation, they consider two peculiarities. EEG and its modifications are used in the initial technique that yields substantial findings out of just three characteristics: the deviations of the impulses and their first & second variants. In the subsequent, a kernel approach is employed to enable an implicit representation of the retrieved characteristics by converting the nonlinear issue to linear space, simplifying the categorization phase and providing a consistent outcome in a short time. S. R. Mousavi et al. [3] talk about a new approach for epilepsy identification based on the autoregressive (AR) model. Bayesian Information Criterion (BIC) establishes the best sequence for an AR system. Afterwards, AR characteristics of electroencephalogram (EEG) signals (from an original EEG dataset at the University of Bonn's epilepsy department) and associated sub-bands (formed via wavelet transform) are recovered using this model. By the use of a multilayer perceptron (MLP) classifier, such values are employed as a characteristic to categorize electroencephalogram (EEG) data into Good health, Pre-ictal (seizure-free), and Ictal (throughout a seizure) categories. Appropriate categorization scores of 91-96 per cent demonstrate the method's effectiveness for epilepsy identification.

In 2017, Zakareya Lasefr et al. [4] produced an EEG-based method for detecting epileptic seizures. Various filtrations will be used to pre-process and analyze the data. The filtered signal would then be divided into four sub-bands. In addition, extracted features are used, and a composite character is created by incorporating multiple elements into just one. Ultimately, researchers employed well-known classification techniques, including SVM (Support Vector Machine), KNN (K nearest Neighbor) and ANN (Artificial Neural Network), to distinguish amongst epileptic & non-epileptic data with 97 per cent efficiency. M. Hüsrev Clasun et al. [5] used a DCNN (Deep Convolutional Neural Network) technique to identify epileptic seizures using EEG signals in 2016. Because it removes the requirement for preprocessing and dimension reduction processes on the dataset, the methodology surpasses earlier work in interpreting EEG signals. The research by Cansu zkan et al. [6] in 2016 focused on autonomously detecting epileptic illnesses based on EEG patterns. Investigations of EEG data in the temporal and frequency region have been performed in the research design, and illness features were found. Consequently, a decision support framework to detect epilepsy is created utilizing an ANN (Artificial Neural Network) and the characteristics acquired. The system's specificity and sensitivity are 94 per cent and 66 per cent, correspondingly. In 2020, Priyanka Mathur et al. [7] introduced the GDFT (Graph Discrete Fourier Transform) as a GSP (Graph Signal Processing) approach for epilepsy identification. To generate GDFT parameters, EEG data values are mapped onto the Eigenspace of the graph's Laplacian matrix. The weighted transparency graph created using EEG signals produces the Laplacian matrix. It suggests edge weights amongst vertices based on Gaussian kernels. The proposed GDFT-derived extracted features are then implemented to use a crisp rule-based categorization to determine the seizure class from the provided EEG input. The suggested GDFT-based characteristics from the Gaussian Weighted Visibility Graph may identify epileptic seizures with 100 per cent efficiency, according to simulated findings.

In 2020, Zixu Chen et al. [8] offered a unique and reliable classifier for epilepsy diagnosis based on a pairing with one Support Vector Machine (SVM). The suggested classifier needs standard and epilepsy patients' information to train, yet it can distinguish ordinary epilepsy or conditions that aren't qualified within the training instances. This notion is relevant and applicable in real-world clinical circumstances because the incoming EEG signals could include various brain disorders, including epilepsy. To verify the efficacy of the suggested architecture, tests were run using the publicly released Bern-Barcelona and CHB-MIT EEG databases. The methodology obtained an accuracy rate of 93 per cent and 94 per cent, correspondingly. Arslan Shahid et al. [9] introduced a new algorithm to identify epileptic seizures relying on SVD (Singular Value Decomposition) in 2013. The SVD is performed in a one-second sliding window of EEG signals, as the singular values were collected and utilized to detect abrupt shifts in the patterns. EEG data from four paediatric patients with 20 seizures were employed to verify the theoretical method.

Early findings show that the single values have a high degree of empathy to alterations in EEG data signals caused by epileptic seizures. This responsiveness could be exploited to create a more accurate seizure sensor than current methods. Dhouha Sagga et al. [10] discuss that seizure identification has now become a focus of attention in the last decade, while EEG has been doing these analyses, research features of activity in the brain, neurological illnesses, and particularly epileptic seizures. To successfully identify epileptic seizures caused by EEG signals, various empirical methodologies have already been used. This study constructed deep learning frameworks for Deep Learning, VGGNET, and ResNet using Convolutional Neural Networks (CNN). Standardized data sets were used for the experiments. The suggested technique was tested on 23 patients from the CHBMIT corpora, with an accuracy rate of 97.60 per cent and 97.32 per cent for ResNet & VGGNET.

In 2010, Han-Yen Chang et al. [11] proposed a new approach for detecting epileptic seizures in aggregated multi-channel EEG recordings incorporating two techniques. A contemporary system, Independent Component Analysis (ICA), would be first modified for the suggested method to distinguish blind sources and extraction of features from aggregated EEG data signals. The Wavelet transform would then be used for those primary signals recovered by ICA for multiple resolutions and multi-level investigation. Furthermore, a wavelet transform-based threshold approach is used to identify epileptic seizures. A set of tests are carried out utilizing various approach combinations, and the results suggest that the recommended system is effective. Kup Sze Choi proposed a segmental categorization method for detecting epileptic seizures in EEG data signals in 2012 [12]. Harender et al. [13] presented a technique for monitoring epileptic seizures from captured EEG signals in normal and epileptic patients in 2017. Simulink was used to represent EEG signal deconstruction using the DWT (Discrete Wavelet Transform) plus statistical calculations, which was then implemented on an FPGA by using Xilinx System Generator. Following DWT decomposition, frequent patterns such as MAV (Mean Absolute Value), Standard Deviation (SD), as well as Average Power (AP) are recovered for epilepsy identification using the KNN (K Nearest Neighbour) classifier. The findings show that for eyes wide open with epileptic seizure datasets with fewer feature extraction, the k-NN classification delivers better precision with Standard Deviation and Standard with Mean Absolute Value.

S. Priyanka et al. [24] proposed an automatic diagnosis technique based on an Artificial Neural Network to diagnose epilepsy from EEG depending on distinct phases of EEG (electroencephalogram) signal levels in 2017. (Ictal, Inter-ictal, Pre-ictal). Characteristics like Average, variance, SD (standard deviation), skew, and kurtosis are retrieved after preprocessing data. Then, the characteristic rating was employed to improve classification performance and minimize dataset dimension. Eventually, NN (Neural Networks) were used to categorize epilepsy depending on the risk factors, and this form of categorization had a 96.9% prediction performance. In 2018, Gang Wang et al. [25] set out to investigate an automatic approach for detecting epileptic episodes to enhance diagnosing and managing patients with clinically intractable epilepsy. For epileptic seizure identification, a new method relies on the DTF (i.e. directed transfer function) technique. The sliding window approach was used to segment EEG (electroencephalogram) recordings, and the DTF method was employed to determine functional brain connections. The overall network flow was determined using DTF derived connection by adding the data flow from a specific EEG field to other channels. Furthermore, the data outflow was allocated as characteristics of an SVM (support vector machine) classification to distinguish interictal from ictal electroencephalogram segments. The new technique has a mean accuracy rate of 98.45 per cent, a mean selective rate of 64.43 per cent, mean

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sensitivities of 93.36 per cent, and a mean specificity of 98.42 per cent as an average classification rate of 95.89 per cent for ten patients with epilepsy. In 2014, Kaveh Samiee et al. [26] developed a strategy dependent on a rational function-based adaptive and localized time-frequency (TF) representation of electroencephalogram data. A unique feature extraction method for epileptic electroencephalogram data is the associated rational DSTFT (Discrete Short-Time Fourier Transform). To distinguish epileptic epochs from seizure-free epochs, these rational DSTFT coefficients are input into an MLP (Multilayer Perceptron) classification method. The suggested system is tested on numerous state-of-the-art feature extraction techniques utilized in offline epileptic seizure identification to see its success. Elly Matul Imah et al. [27] examined several ML (Machine Learning) methods for epilepsy seizure diagnosis using EEG signals in 2017. Generalized Relevance Learning Vector Quantization, SVM (Support Vector Machine), Backpropagation, RF (Random Forest), Wavelet, PCA extraction, and classification techniques are examined in this work. The EEG data included in this investigation were taken from a University of Bonn-developed EEG CYang Li et al. [28] suggested a new and localized time-frequency recognition in electroencephalogram data using MRBF (multiscale radial basis functions) as well as MPSO (Modified Particle Swarm Optimization) to improve time-frequency resolution, which would be a new MRBF-MPSO schema for time-frequency extracting features for epileptic electroencephalogram signals.

Yissel Rodriguez Aldana et al. [29] present a system for detecting nonconvulsive seizures to diagnose non-convulsive status epilepticus. K-Nearest Neighbour (KNN), Radial Basis SVM, and Linear Discriminant Analysis classification algorithm are employed to distinguish between regular and seizure electroencephalograms (EEGs). The CPD (Canonical Polyadic Decomposition) and BTD (Block Term Decomposition) of EEG information recorded as a third-order tensor yield the classification parameters. Wavelet or Hilbert-Huang transforms employed to convert the EEG into a vector. The methodology is validated on a scalp EEG dataset of 139 seizures of various durations. Salim Rukhsar et al. [30] introduced a modified approach for classifying ictal (Epileptic seizure) and seizure-free EEG data in 2017. The method is used for an epoch over the network to extract features. The technique detected an epileptic seizure in 0.1 seconds with a level of achievement of 100 per cent sensitivity, 100 per cent specificity, and 100 per cent accuracy.

Md. Khayrul Bashar et al. [31] proposed a supervised machine learning (ML) technique to distinguish non-ictal (healthy, preictal, as well as interictal), as well as ictal (while seizure) brain functions from EEG data signals in 2016. To diagnose brain epilepsy, numerous time and time-frequency domain variables are collected from EEG data signals and presented to an LDA (Linear Discriminant Analysis) and a nonlinear SVM (Support Vector Machine) classification algorithm. An initial trial with two datasets of EEG data using 'focal" and 'nonfocal' pathways (50 EEG data each set, every 10 seconds duration) of 5 respondents demonstrates that employing a composite of time-frequency domain variables, epilepsy classification performance is 79.20 per cent. EEG data signals obtained from healthy individuals and EEG data collected from epileptic patients throughout epileptic episodes were categorized by Hasan Polat et al. in 2016 [32]. The Hilbert and wavelet transforms were used individually in the classification stage to retrieve characteristics from the EEG data signals. They utilized the same statistical properties to minimize the dimension of the feature vectors obtained by both procedures. The classification approach utilized was KNN (K-nearest neighbour). The KNN technique was used to individually classify the Wavelet and Hilbert transform relevant features. Muhammad U. Abbas et al. [33] used a deep learning architecture to identify epilepsy in an EEG data signal in 2019. With up to 95% efficiency, the suggested Long Short-Term Memory classifier recognizes three types of data signals. Its accuracy climbs to 98 percent for the Binary classification model, including the identification of inter-ictal and ictal alone. Puja A. Chavan et al. [34] detected the seizure by classifying focal and non-focal EEG signals using HLO-HMM based classification technique.

By using the freely released university of Bonn electroencephalogram dataset, Ashwani Kumar Tiwari et al. [35] presented a scheme was researched for the four well-known classification tasks: (a) regular and epileptic seizure, (b) epileptic seizure as well as seizure-free, and (c) regular, epileptic seizure, as well as seizure-free, (d) epileptic seizure as well as non-seizure electroencephalogram data signals. The accuracy of the research outcomes in categorizing has been

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based on existing approaches for categorizing the challenges stated previously. Furthermore, testing on some other electroencephalogram corpora demonstrates that the method efficiently classifies epileptic and seizure-free electroencephalogram data signals. For actual epileptic seizure identification, the suggested technique focused on LBP calculated at important aspects is simple and easy to apply. Lasitha S. Vidyaratne et al. [36] proposed a new patient-specific automated epileptic seizure beginning identification method that uses both head and intracranial electroencephalograms in 2017. With 96 per cent sensitivity, 0.1/hr average false detection accuracy, and 1.89s average recognition delay, the suggested model benefits seizure onset identification. The categorization precision produced from evaluating short-term information is 99.8%. These findings show that the proposed method works correspondingly with short-term and long-term electroencephalogram signal analyses collected in the scalp and intracranial modes.

Cher Hau Seng et al. [37] developed a linear Support Vector Machine classifier in 2012 to recognize and identify seizures in EEG data signals using very few simple variables, including average, variance, Df, and mean power spectra. A standard EEG dataset is used to test the Support Vector Machine classifier. Categorization rates of up to 98 per cent were attained using a composite of these criteria. The suggested classifier is highly scalable enough to be used in a seizure surveillance system because it only uses a few superficial characteristics. In 2016, Sabrina Ammar and colleagues [38] used Single Channel as well as the Wavelet transform (WT) to identify epileptic episodes that use the WT as well as the Deep Learning (DL) Machine. The goal is to develop a method that needs the fewest sensor nodes while reducing calculation resources and time. Preprocessing, extraction and classification using the WT, and categorization using the Deep Learning Machine are the three processes in the decision-making procedure. They used only the FT10-T8 band to assess the developed technique on three distinct data sets from the CHB-MIT scalp EEG collection. The suggested methodology obtained an accuracy of 94.85% in categorization.

Tessy E et al. [39] employed an automated new approach to analyze the EEG output and identify epileptic seizure behaviour in 2016. Using a publicly released database, the suggested technique is validated using two time-domain characteristics, line length and power. For identifying EEG data signals, categorization techniques such as a) QDA (Quadratic Discriminant Analysis), b) KNN, and c) Linear discriminant analysis (LDA) are employed, and their activity is evaluated using sensitivities, specificity, and precision. When the outcomes of the classification models are examined, it is shown that the K-nearest neighbour classifier outperforms another two. The K nearest neighbour classifier achieves an accuracy rate of 94.4 per cent to 100 per cent, and the excellent classification outcomes validated the technique's success. In 2012, Azian Azamimi Abdullah et al. [40] developed an artificial neural network to construct a method that can diagnose epilepsy depending on EEG signals as the extraction of features approaches; the Discrete Wavelet Transform (DWT), as well as FFT (Fast Fourier Transform), were used. These characteristics are fed into a feedforward NN with a backpropagation training technique to obtain classification performance. The DWT approach has a 97 percent recognition rate with 10000 epochs, whereas the Fast Fourier Transform technique has 53.889 per cent accuracy. The maximum accuracy, 98.889 per cent, comes from combining Discrete Wavelet Transform and FFT-derived characteristics. The classification performance relates to the number of epochs and extracted elements. A higher number of generations results in a longer reaction time when training the net. Lorena Orosco et al. [41] introduced an epileptic seizure categorization approach based on aspects of EEG recordings' EMD in 2010. Various techniques of BCI emotions classification for EEG signals using deep learning are described in Puja A. Chavan et al. [42].

Human activity recognition (HAR) may be used efficiently to identify abnormal behaviours and allow early diagnosis of epileptic seizures before they worsen [43]. A variety of methods for detecting unusual behaviour have been studied in recent academic studies [44], such as ambient instrument approaches, sensor-based strategies, and wearable technology. Verification of action identification is ensured by the enabled notification system. However, careful examination and exact feature pattern capture are necessary for accurate detection of these behaviours [45].

Because of its affordability, mobility, and capacity to display unique frequency-dependent patterns, EEG signals are favoured [46]. The electroencephalogram (EEG) is a measuring method that records voltage variations brought on by the ionic flux of neurons to represent the

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bioelectric activity of the brain. Accurately identifying epileptic convulsions requires long-term signal capture, which may be challenging since numerous channels are needed for storage. Concerns about wearable devices' energy consumption and data storage limitations have also been brought up in studies, which makes developing seizure predicting algorithms more difficult [47].

Neural networks of the CNN type are often used in supervised learning. The unique design of CNNs connects every neuron in one layer to every other layer's neuron. An activation function converts each neuron's input into an output [48]. Sparsity, or having a lot of zeros, and the activation function's capacity to transfer gradients to lower layers during backpropagation are two important characteristics that affect CNN performance. In general, CNNs use sparse activation functions in conjunction with their specialised architecture to efficiently train data representations, such as pictures, for supervised learning tasks like classification. Pooling techniques are often used in CNNs to reduce dimensionality. Max-pooling and average-pooling are two often used pooling methods that help to extract the most important characteristics from the data.

One method used to evaluate a classification model's performance is called k-fold cross-validation (k-CV) [49]. Using this approach, a dataset that has been gathered from one or more sources is divided into subsets of k that are about equal in size, separate, and nonoverlapping. The model is trained on the remaining k − 1 subgroups and then evaluated on each of these subsets. Calculating the mean of many performance metrics—including accuracy, precision, recall, and F-measure—that are all obtained from the k-CV procedure yields the model's overall performance.

Gap Analysis

According to the aforementioned analysis, we were able to identify a few gaps and issues that occur both during installation and after system performance evolves. These are listed below.

- Different feature extraction and selection methods produce redundant features, which raise the error rate and decrease system accuracy.
- Using several hidden layers causes memory problems in traditional LSTM approaches.
- While increasing the number of convolutional layers will increase accuracy, it will also increase time complexity. In order to demonstrate improved temporal complexity with respectable accuracy, we must develop a solution for these problems [17].
- When binary and static characteristics from EEG data are employed in classification, redundant features may result in a high false positive ratio [25].
- Numerous studies have used binary and LS-SVM classification to classify signals, but these systems continue to have problems with detection accuracy and time complexity [21].

3. PROPOSED SYSTEM

Problem Formulation

The ability to detect seizures in their early stages is crucial for effective intervention. However, distinguishing preictal (before a seizure) and ictal (during a seizure) states from normal brain activity remains a complex problem. Early detection could significantly improve patient outcomes by enabling timely intervention. The another major problem is achieving a balance between sensitivity and specificity (minimizing false positives) is challenging. Algorithms must be fine-tuned to avoid unnecessary interventions or missed seizures, both of which can have serious consequences for patients.

Proposed System Design

This study used hybrid DL (Deep Learning) techniques to create and establish a system for efficient epileptic illness diagnosis, forecasting, and categorization. This study shows how Convolutional Neural Networks and Long Short-Term Memory can combine to classify EEG data completely. As a result, our paper aims to explore and examine different deep learning (DL) and ML (Machine Learning) algorithms for EEG data categorization. We aim to use multiple deep learning technologies such as ALEXNET, VGGNET, and RESNET to create a Convolutional Neural Network algorithm for extracting features. This research aims to create a Long, Short Term

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Memory classification method using Convolutional Neural Network derived elements for unit testing and training. As a result, we want to make a deep hybrid learning (DL) model that can predict and classify epileptic conditions in actual time.

To examine the complete system utilizing supervised learning techniques in the conducted study, we first collect information from the brain as EEG data signals. System uses the Convolutional Neural Network (CNN) and LSTM algorithms to collect numerous features from the data and create the trained system. The program's goal is to detect epileptic disorder using EEG signals. Categories every input data with its tag in the testing system and display the efficiency of the process.

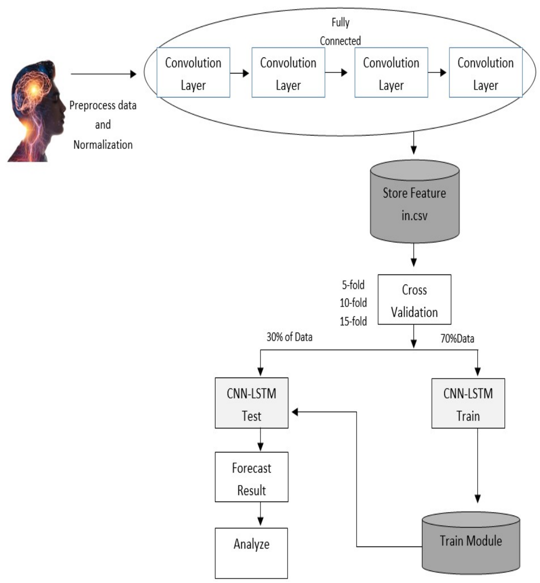


Figure 1: Proposed Systems Architecture for Epilepsy Seizure Detection using CNN-LSTM

The proposed system architecture is illustrated in the following figure 1. The presented work employed the CNN-LSTM classification method to classify epileptic illnesses. It is a supervised learning algorithm primarily used during categorization and regression research. The categorization, widely employed for visual recognition issues, works exceptionally well in aspect-based app identification and hue categorization. Encourage vector machines aren't necessarily better than most other ML (machine learning) techniques; nonetheless, they are at the cutting edge of technology, with a wealth of ongoing theory and practice research. Several experts suggest CNN-LSTM be a superior method for generating ranks. The parameters of the EEG incoming data are placed into the classification algorithms, as well as the epileptic sickness is categorized using a hyperplane as well as the epileptic illness detected. Unique methods from the training dataset were collected during the training phase, and they created a trained framework consequently. An identical feature selection method was used on the testing corpora, obtaining each picture's characteristics as required. The procedure of calculating weight involves finding similarities among train and test characteristics. It is a sub-process that evaluates the correlation between two selected features. The weight parameter determines sentiment labels based on the want threshold (Th) limit. The initial weight is 0, and the users can set the Th.

The final prediction has divided the entire input data into four distinct categories. The decreased small-scale classifier is activated by the epilepsy diagnosis in the top channel and may be used to identify the precise location of impairment inside an image. The following is a discussion of every structure's comprehensive explanation that makes up the suggested framework.

CNN Architectures: The networks that are tested in this test include MobileNet V1, VGG16, and a shallow net. The details of its description will be covered in the debate that follows:

Shallow Net: The objective of the shallow network was to set a benchmark against which the effectiveness of the transfer learning technique could be assessed. It is important to note that the dataset was inadequate for effectively understanding the feature space at this site. Therefore, the results for this network should be approached with care. A neural network comprising three convolutional layers and two fully connected layers was constructed and then trained for the purpose of four-way classification. Figure 2 illustrates this network.

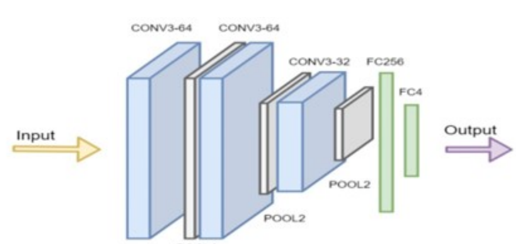


Figure 2: Framework of Shallow Net

VGG16: The VGG16 network will undergo transfer learning after being trained on the IOT dataset. The selection was made. This alternative is often favored because of its high efficiency and simple design. The VGG16 model consists of a grand total of 41 layers, out of which 16 layers possess learnable weights. The model consists of 13 convolutional layers and three fully linked layers. Throughout the training procedure, only the completely linked layers were initialized and then retrained. This was done to ensure the preservation of the pre-trained weights. Additionally, an experiment was conducted to assess if fine-tuning the last convolutional layer after training the fully connected layers would lead to improved performance. However, the findings did not demonstrate a significant improvement.

MobileNet V1: In situations when there's a lack of data, it is often beneficial to use a framework that is simpler and less resource-intensive. The MobileNet test will be applied to it, since MobileNet comprises a collection of efficient models designed for mobile and embedding vision applications. MobileNet uses a simplified design that incorporates depth-wise separable convolutions to enhance the computational efficiency of the network. Furthermore, the width multiplication and the dimension multiplier are used to achieve a balance between efficiency and accuracy, alongside to the i.e. nomenclature. MobileNet has a much lower parameter count 142 M. parameters compared with VGG16, which has 138 M. parameters

Deep Convolutional Neural Network (DCNN)

The classification algorithm used for the proposed system is given below. In accordance with the directed learning approach, our dataset is divided into two distinct phases: the training dataset and the test dataset. The cross validation of tenfold was used to partition the data, with 70% of the data used for training and 30% for testing. The following method outlines a training mechanism used for component training throughout implementation.

Training: CNN Training

Input : Training Dataset *TrainData[]*, Testing Dataset *TestData[]*, iteration as *epoch_Size,*

Output : Generated rules by respective classifier *Training_Rules[]*

Step 1: *for each all training data*

$$Extracted\_Attribute[i][j] \sum_{i=0,j=0}^{n} (a_{[i]}, a_{[j]} \ldots\ldots a_{[n]}, a_{[n].})$$

Step 2*:* *Generate instance for CNN as objCNN*

T_Rules[] ← *objCNN.Trainclassifier (Extracted_Attribute[m][n])*

Step 3 : *for each all testing data*

$$Extracted\_Test\_Data[i][j] \sum_{i=0,j=0}^{n} (a_{[i]}, a_{[j]} \ldots\ldots a_{[n]}, a_{[n].})$$

Step 4 : *Apply all classifiers on test data using above training rules*

Pred1[] ← *CNN.Buildclassifier* $(Extracted_{Test_{Data[m][n]}}$, *Master_Training_List[])*

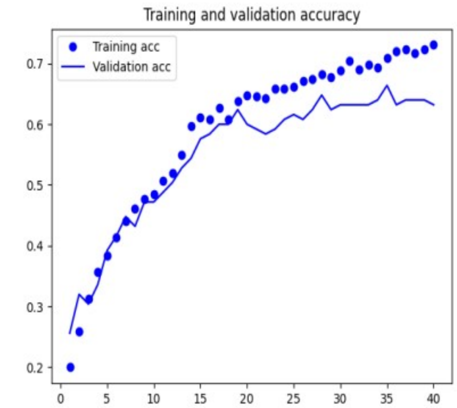
Step 5 : *C_Matrix[]* ← *Calc_Accuracy(Pred1[])*

Step 6 : *Review C_Matrix[]*

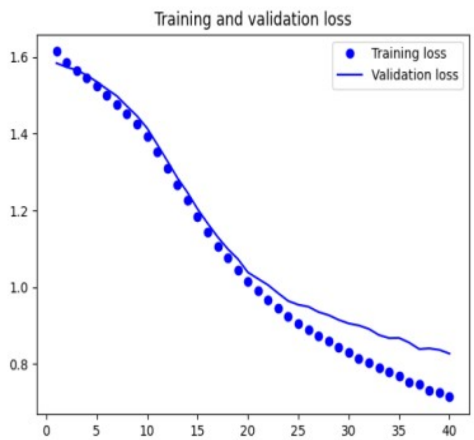
Here, the above algorithm works to generate the training rules as well as classify the test data accordingly. In step 2, the *T_Rules[]* are the training rules that are generated by selective classifiers. The rules were generated based on an extracted hybrid feature set. However, *Extracted_test_dada[]* is the extracting features set that are extracted from the testing dataset. In the dense layer, the evaluation has been done, which I set as 4. The *T_Rules[]* and *Extracted_test_dada[]* are used for generated prediction results. Finally, evaluation has been done to calculate accuracy, precision, recall, and F-score.

4. RESULT AND DISCUSSION

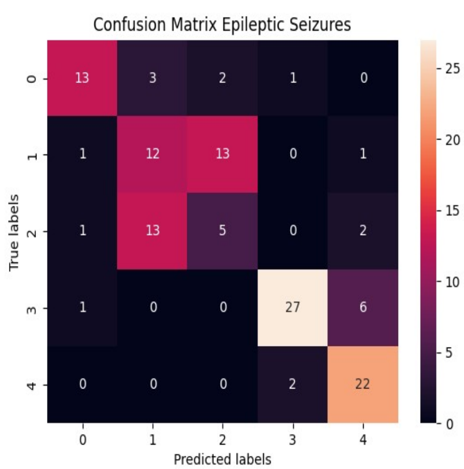
The proposed implementation has done with python open-source environment. The 3.7 python framework has used with deep CNN using VGGNET model. The Figures 3 to 7 shows the results for training and validation accuracy with losses for each iteration. Generally, five iterations are performed on the EEG dataset using the proposed CNN. The subfigure of each figure demonstrates the confusion matrix for the respective iteration process. The highest average accuracy we achieve is around 82.5% for the entire test dataset.



(a)

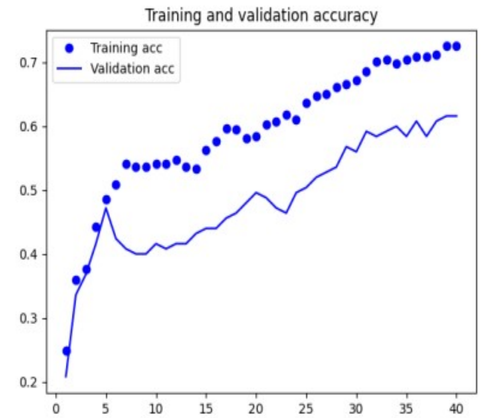


(b)

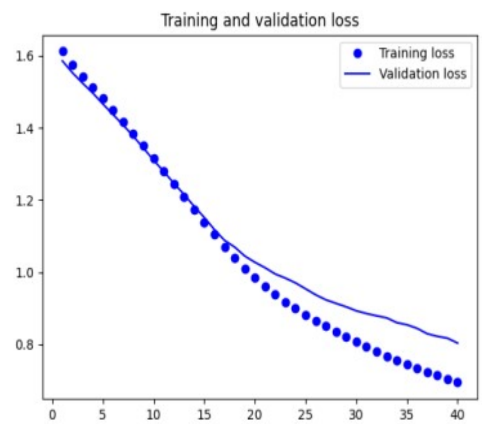


(c)

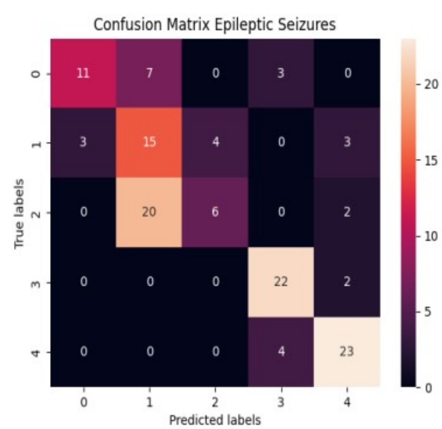
Figure 3: Iteration 1st (a) Training and Validation Accuracy; (b) Training and Validation Loss; (c) Confusion Matrix Generation



(a)



(b)



(c)

Figure 4: Iteration 2nd (a) Training and Validation Accuracy; (b) Training and Validation Loss; (c) Confusion Matrix Generation

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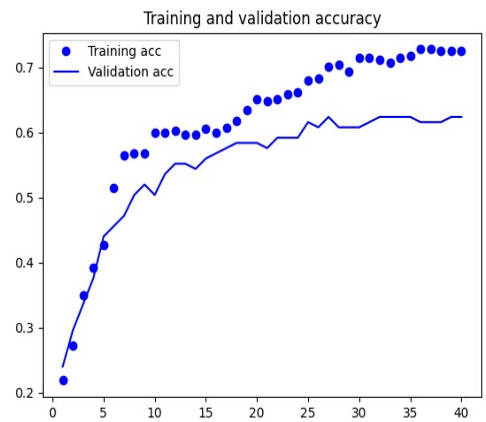
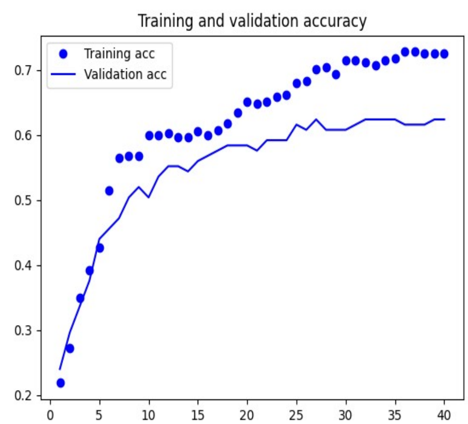
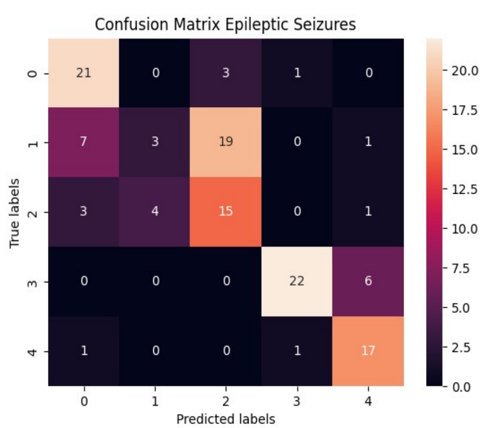


(a)

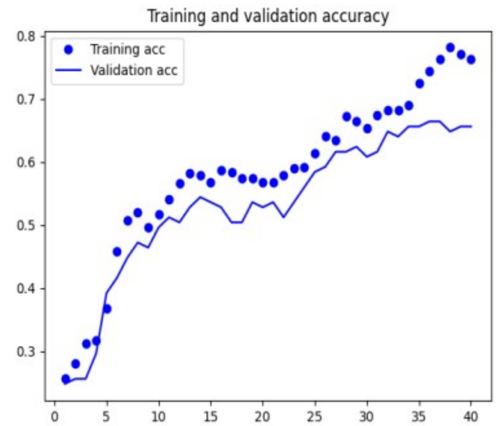


(b)

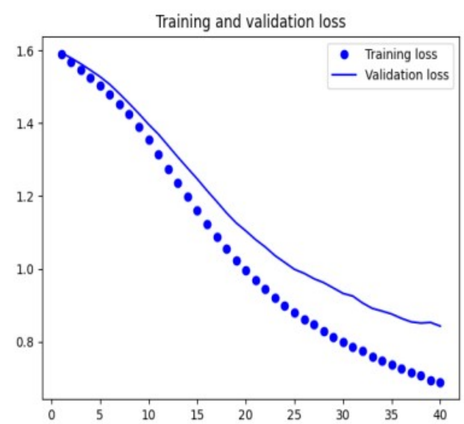


(c)

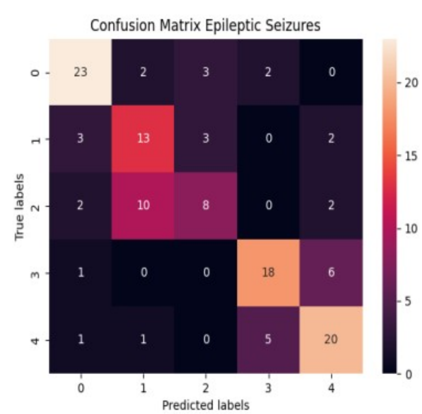
Figure 5: Iteration 3rd (a) Training and Validation Accuracy; (b) Training and Validation Loss; (c) Confusion Matrix Generation



(a)



(b)



(c)

Fig. 6 Iteration 4th (a) Training and Validation Accuracy; (b) Training and Validation Loss; (c) Confusion Matrix Generation

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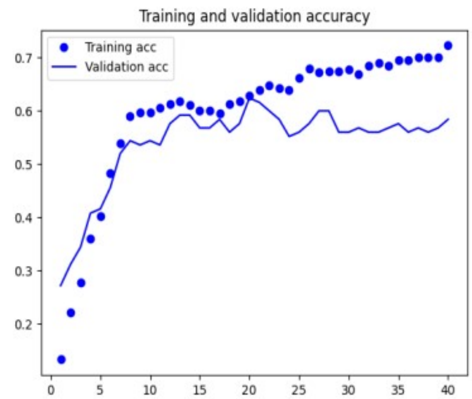
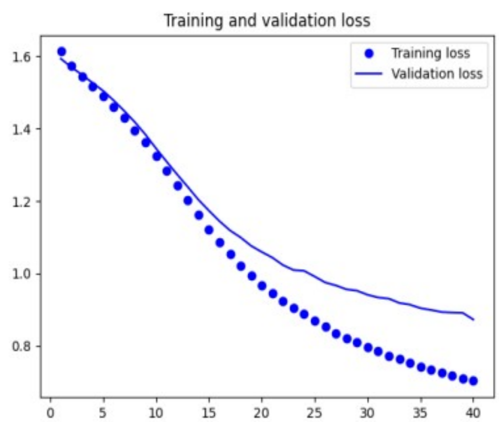
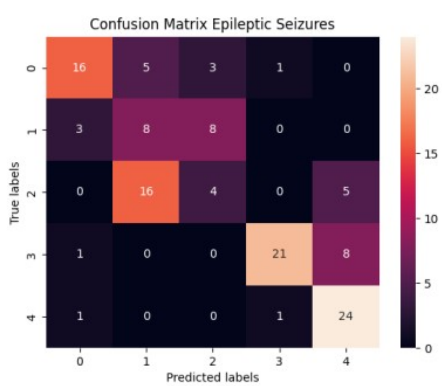


(a)



(b)



(c)

Fig. 7 Iteration 5th (a) Training and Validation Accuracy; (b) Training and Validation Loss; (c) Confusion Matrix Generation

According to the above experiment, the figures 3, 4, 5, 6, 7 demonstrate the testing accuracy and the loss of the entire data set. The convolutional neural network and LSTM hybrid approach have been utilized to detect epilepsy. Various features are extracted and optimized in the pulling layer in the convolutional layer. Multiple convolutional layers perform similar tasks, and the dense layers predict the final classification accuracy. The proposed algorithm achieves 82.5% detection accuracy for a real-time EEG dataset.

5. CONCLUSION

This research proposed an epileptic seizure detection and prediction algorithm utilizing deep learning approaches. In general, electrical brain activity has become a highly sought-after topic of scientific inquiry to investigate critical disorders of the human brain. For the prediction of epileptic seizures, we suggested five models (CNN-LSTM with ResNet-100). According to the results, our approaches based on the fusion of CNN and LSTM have an accuracy rating of 82.5%. In the future, further seizure prediction can be enhanced to boost accuracy, allowing clinicians to schedule treatment more promptly and accurately. It may expand this study by using EEG data, upgrading classifiers, and employing more straightforward feature extraction approaches. The major benefit of the proposed model is that it can detect early epileptic detection and classification of EEG signals. The above results also demonstrate that the system can reduce the error rate as well as enhance the accuracy of the entire module on various testing datasets.

REFERENCES:

[1] Shreya Gautam, Shreety Sriya and Tanuj Chauhan. “Focal and Non-focal Epilepsy detection using EEG signals via Empirical Mode Decomposition”, 2015, IEEE.

[2] Zayneb Brari and Safya Belghith. “A new method for the detection of epilepsy and epileptic seizures based on the variance of EEG signals and its derivatives with a simple kernel trick”, 2020 4th International Conference on Advanced Systems and Emergent Technologies (IC_ASET), IEEE.

[3] S. R. Mousavi, M. Niknazar and B. Vosoughi Vahdat. “Epileptic Seizure Detection Using AR Model On EEG Signals”, 2008, CIBEC'08, IEEE.

[4] Zakareya Lasefr, Ramasani Rakesh Reddy and Khaled Elleithy. “Smart Phone Application Development for Monitoring Epilepsy Seizure

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Detection based on EEG signal Classification", 2017, IEEE.

[5] M. Hüsrev Cılasun and Hülya Yalçın. "A Deep Learning Approach to EEG based Epilepsy Seizure Determination", 2016, IEEE.

[6] Cansu Özkan, Seda Doğan, Tuğçe Kantar, Mehmet Feyzi Akşahin and Aykut Erdamar. "Detection of Epilepsy Disease From EEG Signals With Artificial Neural Networks", 2016, IEEE.

[7] Priyanka Mathur. "Graph Signal Processing of EEG signals for Detection of Epilepsy", 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN), IEEE.

[8] Zixu Chen, Guoliang Lu, Zhaohong Xie and Wei Shang. "A unified framework and method for EEG-based early epileptic seizure detection and epilepsy diagnosis", 2020, IEEE.

[9] Arslan Shahid, Nidal Kamel, Aamir Saeed Malik and Munsif Ali Jatoi. "Epileptic Seizure Detection using the Singular Values of EEG Signals", 2013 ICME International Conference on Complex Medical Engineering May 25 - 28, Beijing, China, IEEE.

[10] Dhouha Sagga, Amira Echtioui, Rafik Khemakhem and Mohamed Ghorbel. "Epileptic Seizure Detection using EEG Signals based on 1D-CNN Approach", 2020 20th international conference on Sciences and Techniques of Automatic control & computer engineering (STA), Sfax, Tunisia, December 20-22, IEEE.

[11] Han-Yen Chang, Sheng-Chih Yang, Sheng-Hsing Lan and Pau-Choo Chung. "Epileptic Seizure Detection in Grouped Multi-Channel EEG Signal Using ICA and Wavelet Transform", 2010, IEEE.

[12] Kup-Sze Choi, Yugu Zeng and Jing Qin. "Using Sequential Floating Forward Selection Algorithm to Detect Epileptic Seizure in EEG Signals", 2012, IEEE.

[13] Harender and R. K. Sharma. "DWT based Epileptic Seizure Detection from EEG signal using k-NN classifier", 2017 International Conference on Trends in Electronics and Informatics ICEI, IEEE.

[14] Saeed Mian Qaisar and Abdulhamit Subasi. "Adaptive Rate EEG Signal Processing for Epileptic Seizure Detection", 2018, IEEE.

[15] Md. Mamun and Mohiuddin Ahmad. "Epileptic Seizure Classification using Statistical Features of EEG Signal", 2017 International Conference on Electrical, Computer and Communication Engineering (ECCE), February 16-18, Cox's Bazar, Bangladesh, IEEE.

[16] Selvin Pradeep Kumar.S and Ajitha.L. "Early Detection of Epilepsy using EEG signals", 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), IEEE.

[17] Ye Yuan. "Detection of Epileptic Seizure Based on EEG Signals", 2010 3rd International Congress on Image and Signal Processing (CISP2010), IEEE.

[18] Murside Degirmenci and Aydin Akan. "EEG based Epileptic Seizures Detection using Intrinsic Time-Scale Decomposition", 2020, IEEE.

[19] L. K. Jayashree and Bondu Venkateswarlu. "EEG Signals in Epilepsy Seizure Detection: An Empirical Study", 2020 Fourth International Conference on Electronics, Communication and Aerospace Technology (ICECA-2020), IEEE.

[20] Zakareya Lasefr, Sai Shiva VNR Ayyalasomayajula and Khaled Elleithy. "An Efficient Automated Technique for Epilepsy Seizure Detection Using EEG signals", 2017, IEEE.

[21] Ali Shahidi Zandi, Manouchehr Javidan, Guy A. Dumont and Reza Tafreshi. "Automated Real-Time Epileptic Seizure Detection in Scalp EEG Recordings Using an Algorithm Based on Wavelet Packet Transform", 2010 Transactions On Biomedical Engineering, Vol. 57, No. 7, IEEE.

[22] L. Wei and C. Mooney. "Epileptic Seizure Detection in Clinical EEGs Using an XGboost-based Method", 2020 Signal Processing in Medicine and Biology Symposium (SPMB), IEEE.

[23] M. Kaleem, A. Guergachi and S. Krishnan. "EEG Seizure Detection and Epilepsy Diagnosis using a Novel Variation of Empirical Mode Decomposition", 2013 35th Annual International Conference of the IEEE EMBS Osaka, Japan, 3 - 7 July

[24] S. Priyanka, Dawa Dema and Dr.T.Jayanthi. "Feature Selection and Classification of Epilepsy from EEG Signal", 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), IEEE.

[25] Gang Wang, Doutian Ren, Dong Wang, Maode Wang and Xiangguo Yan. "EEG-based Detection of Epileptic Seizures through the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Use of a Directed Transfer Function Method", 2018, IEEE.

[26] Kaveh Samiee, Peter Kov´acs and Moncef Gabbouj. "Epileptic Seizure Classification of EEG time-series using Rational Discrete Short Time Fourier Transform", 2013, IEEE Transactions On Biomedical Engineering.

[27] Elly Matul Imah and Arif Widodo. "A Comparative Study o f Machine Learning Algorithms for Epileptic Seizure Classification on EEG Signals", 2017, IEEE.

[28] Yang Li, Xu-Dong Wang, Mei-Lin Luo, Ke Li, Xiao-Feng Yang and Qi Guo. "Epileptic Seizure Classification of EEGs using Time-Frequency Analysis based Multiscale Radial Basis Functions", 2017, IEEE.

[29] Yissel Rodrıguez Aldana, Borbala Hunyadi, Enrique J. Maranon Reyes, Valia Rodrıguez Rodrıguez, and Sabine Van Huffel. "Nonconvulsive Epileptic Seizure Detection in Scalp EEG Using Multiway Data Analysis", 2018, IEEE.

[30] Salim Rukhsar, Haroon Rehman, Yusuf Uzzaman Khan and Ayesha Tooba Khan. "Detection of Epileptic Seizure in EEG Signals Using Phase Space Reconstruction and Euclidean Distance of First-Order Derivative", 2017, Proceedings of the International Conference on Inventive Computing and Informatics (ICICI 2017) IEEE.

[31] Md. Khayrul Bashar, Faruque Reza, Zamzuri Idris and Hiroaki Yoshida. "Epileptic Seizure Classification From Intracranial EEG Signals: A Comparative Study", 2016, IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES) .

[32] Hasan Polat and Mehmet Sirac Ozerdem. "Epileptic Seizure Detection from EEG Signals by Using Wavelet and Hilbert Transform", 2016, IEEE.

[33] Muhammad U. Abbasi, Anum Rashad, Anas Basalamah and Muhammad Tariq. "Detection of Epilepsy Seizures in Neo-Natal EEG Using LSTM Architecture", 2019, IEEE

[34] Puja A. Chavan, Sharmishta Desai, Effective Epileptic Seizure Detection by Classifying Focal and Non-focal EEG Signals using Human Learning Optimization-based Hidden Markov Model, Biomedical Signal Processing and Control, Volume 83, 2023, 104682, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2023.104682.

[35] Ashwani Kumar Tiwari, Ram Bilas Pachori, Vivek Kanhangad and B. K. Panigrahi. "Automated Diagnosis of Epilepsy using Keypoint Based Local Binary Pattern of EEG Signals", 2016, IEEE.

[36] Lasitha S. Vidyaratne and Khan M. Iftekharuddin. "Real-Time Epileptic Seizure Detection Using EEG", 2016, IEEE.

[37] Cher Hau Seng, Ramazan Demirli, Lunal Khuon and Donovan Bolger. "Seizure Detection in EEG Signals Using Support Vector Machines", 2012, IEEE.

[38] Sabrina Ammar and Mohamed Senouci. "Seizure Detection with Single-Channel EEG using Extreme Learning Machine", 2016, 17th international conference on Sciences and Techniques of Automatic control & computer engineering, IEEE.

[39] Tessy E, Muhammed Shanir P. P and Shaleena Manafuddin. "Time Domain Analysis of Epileptic EEG for Seizure Detection", 2016, International Conference on Next Generation Intelligent Systems (ICNGIS), IEEE.

[40] Azian Azamimi Abdullah, Saufiah Abdul Rahim and Adira Ibrahim. "Development of EEG-based Epileptic Detection using Artificial Neural Network", 2012, International Conference on Biomedical Engineering, Penang, IEEE.

[41] Lorena Orosco, Agustina Garcés Correa and Eric Laciar. "Multiparametric Detection of Epileptic Seizures using Empirical Mode Decomposition of EEG Records", 2010, 32nd Annual International Conference of the IEEE EMBS Buenos Aires, Argentina, IEEE.

[42] Puja A. Chavan, Dr. Sharmishta Desai. (2021) "A Review on BCI Emotions Classification for EEG Signals Using Deep Learning", Recent Trends in Intensive Computing, ADVANCES IN PARALLEL COMPUTING, IOS Press 39: 544-551

[43] Ayman, U.; Zia, M.S.; Okon, O.D.; Rehman, N.U.; Meraj, T.; Ragab, A.E.; Rauf, H.T. Epileptic Patient Activity Recognition System Using Extreme Learning Machine Method. Biomedicines 2023, 11, 816.

[44] Mekruksavanich, S.; Phaphan, W.; Hnoohom, N.; Jitpattanakul, A. Attention-Based Hybrid Deep Learning Network for Human Activity Recognition Using WiFi Channel State Information. Appl. Sci. 2023, 13, 8884.

[45] Shoeibi, A.; Khodatars, M.; Ghassemi, N.; Jafari, M.; Moridian, P.; Alizadehsani, R.; Panahiazar, M.; Khozeimeh, F.; Zare, A.; Hosseini-Nejad, H.; et al. Epileptic Seizures

Detection Using Deep Learning Techniques: A Review. Int. J. Environ. Res. Public Health 2021, 18, 5780.

[46] Shoka, A.; Dessouky, M.; El-Sayed, A.; Hemdan, E.E.D. EEG seizure detection: Concepts, techniques, challenges, and future trends. Multimed. Tools Appl. 2023, 82, 42021–42051.

[47] Wang, Z.; Yang, J.; Wu, H.; Zhu, J.; Sawan, M. Power efficient refined seizure prediction algorithm based on an enhanced benchmarking. Sci. Rep. 2021, 11, 23498.

[48] Varone, G.; Boulila, W.; Driss, M.; Kumari, S.; Khan, M.K.; Gadekallu, T.R.; Hussain, A. Finger pinching and imagination classification: A fusion of CNN architectures for IoMT-enabled BCI applications. Inf. Fusion 2023, 101, 102006.

[49] Bragança, H.; Colonna, J.G.; Oliveira, H.A.B.F.; Souto, E. How Validation Methodology Influences Human Activity Recognition Mobile Systems. Sensors 2022, 22, 2360.