Design of a Dense Layered Network Model for Epileptic Seizures Prediction with Feature Representation

Summia Parveen[1]
Assistant Professor, Department of Computer Science and Engineering
Sri Eshwar College of Engineering, Coimbatore, India

S. A. Siva Kumar[2]
Associate Professor, Department of Electronics and Communication Engineering
Dr. N. G. P. Institute of Technology, Coimbatore, India

P. MohanRaj[3]
Assistant Professor, Department of Electronics and Communication Engineering
Sri Ramakrishna Engineering College, Coimbatore, India

Kingsly Jabakumar[4]
Assistant Professor, Department of Electronics and Communication Engineering
Christ the King Engineering College, Coimbatore, India

R. Senthil Ganesh[5]
Assistant Professor, Department of Electronics and Communication Engineering, Sri Krishna College of Engineering and Technology, Coimbatore, India

***Abstract*—Epilepsy is a neurological disorder that influences about 60 million people all over the world. With this, about 30% of the people cannot be cured with surgery or medications. The seizure prediction in the earlier stage helps in disease prevention using therapeutic interventions. Certain studies have sensed that abnormal brain activity is observed before the initiation of seizure which is medically termed as a pre-ictal state. Various investigators intend to predict the baseline for curing the pre-ictal seizure stage; however, an effectual prediction model with higher specificity and sensitivity is still a challenging task. This work concentrates on modelling an efficient dense layered network model (DLNM) for seizure prediction using deep learning (DL) approach. The anticipated framework is composed of pre-processing, feature representation and classification with support vector based layered model (dense layered model). The anticipated model is tested for roughly about 24 subjects from CHBMIT dataset which outcomes in attaining an average accuracy of 96% respectively. The purpose of the research is to make earlier seizure prediction to reduce the mortality rate and the severity of the disease to help the human community suffering from the disease.**

Keywords—Epilepsy seizure; pre-ictal state; deep learning; feature representation; vector model

I. Introduction

A patient affected continuous seizures due to Epilepsy, a neurological order. This disease is afflicted on more than 1% of the world population. Medicines or surgical therapy were given to the patients afflicted by this disease [1]. In more than 40% cases, seizures cannot be manipulated with the recent models which consist of surgical procedures [2]. Hence, it is immensely vital that seizures can be treated with the help of medication by anticipating the consequent seizures before they arise. To sense brain activity, EEG signals are monitored [3]. Denoting EEG electrodes on the tissue termed intracranial EEG signals recorded these signals. The advancements in electrical signals of the internal brain are noticed by EEG recording and it is termed as scalp EEG or electrodes implantations of internal brain.

These states consist of preictal state, i.e. 30 minutes a seizure takes place. Then, Ictal state, i.e. the seizures' starting and ending are the same period and finally, post-ictal state, i.e. period after the seizure occurs [4]. The initial state gives knowledge about the starting of a seizure, which is beneficial for us; as it is the period before the seizure happens. Identifying preictal state can assist in eliminating seizures with treatment. Multiple EEG signal generation channels for interictal, preictal, and ictal states are exhibited sequentially [5]. There is a contradiction among these two states based on amplitude and frequency. It substantially enlarges in the preictal state on the contrary to interictal state. This case instigates predicting epileptic seizures successfully by categorizing interictal and preictal signals.

After digitization with a sampling rate from 200Hz to 5000Hz, EEG signals are captured with headsets and processed. These signals are clarified during the seizure onset by a neurologist on the particular software [6]. Before preictal seizure onset, the individuals' state is examined for 30 to 90 minutes. It is the next state of post-ictal state and ends before preictal state. However, interictal is the normal brain state. The aim is to accomplish preictal and interictal state classification, as mentioned previously [7]. Numerous researchers have suggested ML and DL approaches for seizures prediction. Pre-processing, features extraction and classification are included in this method. Pre-processing is terminated in the initial step to detach noise and accelerate

SNR. EEG signal filtering in the time domain with notch and bandpass Butterworth filters are added as common pre-processing methods. When enforced on EEG signals, the spatial and optimized pattern filter renders superior SNR. To preprocess EEG signals, EMD is beneficial. We can increase the SNR as it affords intrinsic mode and preserves low-frequency components. To make the proper victual in CNN, Wavelet and Fourier transform is also utilized [8]. Features are removed, and relevant features are preferred after noise removal, which affords high interclass and intra-class variance. For forecasting epileptic seizures, researchers have removed handcrafted features in both temporal and spectral features. The first four statistical moments are embraced in temporal features, PSD and spectral moments are embraced as special features [9]. After the progression of DL approaches, automatic feature extraction with CNN has also been utilized by many researchers and these features are removed based on class information. After feature selection with the CNN model, classification is executed. Various investigators utilized SVM, RF, K-NN, NB and MLP for classifications. In some cases, CNN, LSTM and RNN can also be utilized for classification, which included in deep learning classifiers [10]. However, there are some flaws over the existing models. The major limitation is the lack of prediction rather than classification. Earlier prediction helps to reduce the mortality rate and proper decision can be done to help the patients to get rid of the disease. This research focuses on modelling a dense layered network for epileptic seizure prediction and evaluates various metrics like sensitivity and specificity. The dense network model alleviates the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters. The purpose of the research is to make earlier seizure prediction to reduce the mortality rate and the severity of the disease to help the human community suffering from the disease. The major contributions of the proposed model are:

1) Initially, an online available dataset known as CHBMIT is considered to perform the analysis for epileptic seizure prediction;

2) Fourier transform is applied for performing feature representation to enhance the quality of prediction;

3) Finally, a dense layered network model is proposed to perform the prediction process. The significance of the model is achieved with metrics like accuracy.

The work is provided as: Section II provides a comprehensive analysis on various prevailing approaches. The methodology is elaborated in Section III and the numerical results are discussed in Section IV. The summary is discussed in Section V.

II. Related Works

EEG signal-processing features extraction and classification are associated with seizure prediction systems. Various ML and DL approaches are proposed by many researchers for forecasting epileptic seizures, manipulating scalp EEG signals and enrol EEG signals with electrodes placed on the patient's scalp. Many researchers in recent years have proposed prediction methods [11]. Three common steps are embraced by all these methods, which comprise EEG signal pre-processing, extracting features from EEG signals and classification between preictal and interictal states.

During EEG signals acquisition, noise is attached, which deals with the SNR of EEG signals, consequently in poor categorization among preictal and interictal states. Various kinds of noise affect EEG signals embracing power line of 50 to 60 HZ baseline noise because of intervention of numerous electrodes and noise annex because of the electrical activity embracing eye movement and heart pulse [12]. Hence, to multiply SNR for progressive outcomes, it is excessively linked to discharge noise as pre-processing step to enlarge SNR, different pre-processing techniques are scheduled by researchers [13]. To eliminate noise, low/high pass filtering is used by author [14]. Using scalp EEG signals for seizure prediction, numerous pre-processing approaches are utilized by researchers [15]. For noise removal, Zandietal, Feietal and Myersetal have utilized Bandpass filtering. To preprocess the dataset in the frequency domain, the author has enforced FFT [16]. In pre-processing of EEG signals, Truongetal has practised short-time Fourier transform. Cause of non-stationary EEG signals, STEFT has been suggested for pre-processing. For pre-processing the signals, both EMD and WT are utilized by [17]. Based on frequency components, EMD separates signals into intrinsic mode functions. Wavelet transforms for pre-processing, Khan et al., have enforced. Using spatial and adaptive filtering, local decomposition and other methods helps in noise extraction from EEG signals [18].

Features are detached after EEG signals pre-processing to classify various seizure states. Utilizing deep learning methods, features can be divided into two ways: extracting handcrafted features is the first, and automated feature extraction is another. Handcrafted features embrace uni- and multivariate features in both the frequency and time domains. Statistical moments define variance, entropy, skewness and kurtosis, entropy, PCA and Lyapunov exponent are embraced in temporal features [19]. Spectral moments and PSD are embraced in special features. Handicraft features have been divided into various seizure prediction methods in recent days, where researchers are embraced zero-crossing intervals, BoW, spectral features in the frequency domain, spatial pattern filtering and for automated feature extraction, some studies have utilized convolutional neural networks [20] – [22]. CNN separating features separate features keeping the target classes beneath consideration with high inter –lasso's variance with the support of CNN in this method. On scalp EEG signals, feature extraction techniques in state-of-the-art seizure prediction methods [23].

Classification between preictal and interictal states is done once the features have been separated from EEG signals. For categorizing EEG signals with seizure prediction, both ML and DL approaches are utilized by researchers. Nearest neighbour, Naive Bayes, support vector machine, Gaussian mixture model, DT, and RT are added to machine learning classification methods. The deep CNN, RNN, and LSTM units are embraced in deep learning classifiers. Variation mixture models are utilized in recent studies. An extreme learning machine and certain threshold to differentiate among interictal and precital classes are utilized for classification and are tried quietly as a classifier support vector machine by [24]. For various seizures classification, convolutional neural networks are also utilized. Currently, researches utilized classification techniques are shown in [25]. The limitations in automatic detection of interictal spikes and epileptic seizures are preferred using the deep learning approach. The major research gap is the lack of accurate prediction of the disease and the computational complexity encountered during the prediction process. Based on these issues, the proposed model intends to reduce the complexity in the prediction process and enhance the accuracy.

III. Methodology

We used the CHBMIT dataset, freely available to the public, to apply our suggested methodology. It is a collection of 24 frontal ECG signals from patients aged 2 to 22. The section that follows gives a thorough summary of this database.

A. Dataset

A patient's EEG signals may be captured using electrodes placed on the forehead (scalp electrode) or by transplanting the electrical stimulation in the brain parenchyma (EEG signals). We utilized a publicly accessible collection of head EEG signals from CHBMIT (ECG recordings) from the pediatric subjects with intractable seizures. This dataset was compiled via a partnership between Children's Hospital Cambridge and Harvard and is freely accessible on Pysionet.org. It contains 22 participants, all humans, comprising 17 and 05, female and male, respectively ranging in age from 1.5 years to 19 years for females and 3 years to 22 years for males. Twenty-three microphones positioned on the scalps of people living with Epilepsy helped capture the dataset. All EDF files were turned to.mat documents using the MATLAB 'edfread' program. The sampling rate for the data was 256 Hz. MATLAB 2020a plays a substantial role in pre-processing and classification approach as the simulation environment is ease of use, it helps to make prediction faster. That participant's material has been separated into numerous files with an hour-long recording. The Preictal state in this country occurs before the onset of the ictal stage. The database is described in full in Table I.

B. Prediction Model

A strategy for predicting seizures begins a few seconds well before the commencement of the seizure, is described here. The suggested method's flowchart is shown in Fig. 1 and Fig. 2. We utilized the publicly available CHBMIT electroencephalographic dataset, which includes 24 people and signals collected with 23 wires and digitized at 256 Hz. The data source is freely accessible for download. "edfread" converts these outputs to mat files. Whitehead wide bandwidth removes background noise from EEG data. After noise reduction, STFT is done to boost the noise ratio and translate signals to the frequency domain. It is possible to extract several individually created univariate and multivariate characteristics in both the time and frequency domains [26]. These traits are not, however, retrieved based on the classification method to which they belong. So we used DNN to extract characteristics. As they are retrieved with the aid of class information taken into account, these characteristics provide superior covariance variance [27]. Following DNN feature extraction, fully linked layers are swapped out for SVM. DNN extracts features whereas SVM classifies interictal & preictal segments. STFT, DNN, and SVM are briefly explained in the following subgroups.

C. Fourier-based Feature Analysis

Short-Time Fourier Transform (STFT) converts the time to frequency domain. Due to non-stationary characteristic of EEG data, STFT produces superior pretreatment results since it catches variations in the signals that last for a brief period. On an equally spaced interval of 30 seconds, we used STFT.

TABLE I. DATASET DESCRIPTION

Type	**Scalp EEG**
Subject	22
Male	5
Female	17
Channel	23
Sampling rate	256
Total seizures	198
Recordings	644

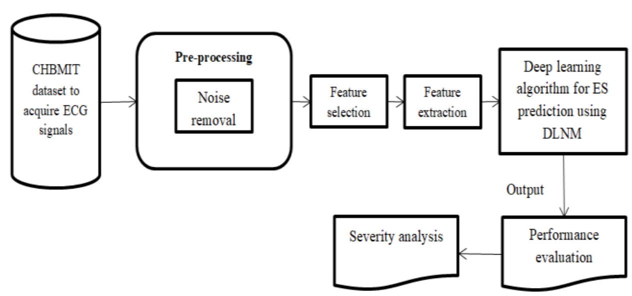

Fig. 1. Block Diagram of Proposed Model.

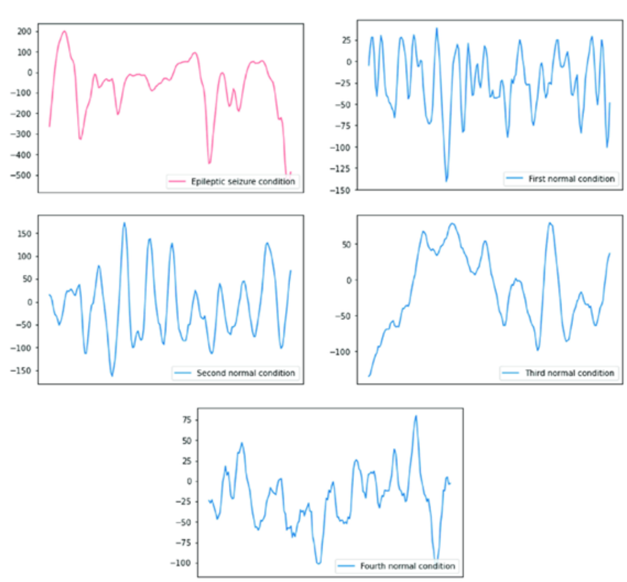

Fig. 2. Epileptic Seizure Dataset based Sample Waveforms.

D. Dense Layered Network Model (DLNM)

This architecture is provided to make the prediction process based on the dataset class labels. The model includes three sections: input, feature representation and output layer for classification purpose. The extracted features are provided as the input to the input layer. The feature representation section helps in extracting the most influencing feature that shows major impact in triggering the disease as in Fig. 3. Finally, the output layer is to extract the outcome. DLNM is frequently employed for input and time-varying series categorization and semantic segmentation [28]. It has many layers: compression, pools, and conventional neural network-based final layers for identification. Eq. (1) & (2) display the DNN updated weights.

$$\Delta W_l(t+1) = -\frac{x\lambda}{r} W_l - \frac{x}{n}\left(\frac{\partial C}{\partial W_l}\right) + m\Delta W_l(t) \quad (1)$$

$$\Delta B_l(t+1) = -\frac{x}{n}\left(\frac{\partial C}{\partial W_l}\right) + m\Delta B_l(t) \quad (2)$$

Here, W stands for weighting, l for layers, and B for bias, while $x, n, m, and\ t$ are regularisation parameters. The artificial neuron, which may be a gaussian, softmax, or linear transfer unit, comes after compression. Eq. (3), (4) & (5) present exponential, softmax and linear transfer unit model parameters.

$$y = \frac{1}{1+e^{-x}} \quad (3)$$

$$\sigma(z) = \frac{e^z}{\sum_{j=1}^{k} e^{z_j}} \quad (4)$$

$$f(x) = \max(0, x) \quad (5)$$

The mathematical notation used in this section is shown in Table II. The layer used to decrease the number of features is called the pooling layer. The two most popular pooling techniques are maximum and average. In this suggested technique, 16 filters (5*5) were used in the convolutional layer (CL), batch normalization with 0.4 dispersion, 32 filters (3*3) is utilized in the second CL, batch normalization, and 64 filters of 3*3 is the third layer. In all layers, an improved activation function non-linear unit is employed. After each convolution operation, batch normalization and convolutional with 2*2 are used. Well, after the third layer, some characteristics combine both classes. Fig. 2 depicts the DLNM used in our suggested strategy for image retrieval. In the suggested method, learnable CNN settings are 32576.

E. Support Vectors for Classification

After extracting DLNM characteristics, we utilized SVM to classify interictal and nine-month states. Linear and non-linear SVMs are the two main categories inside which SVMs may be separated. We can discover support vectors and build a maximum margin using slope and intercept if we have feature space variables. They are known as linear SVMs. We cannot know when to use a linear barrier since data cannot be linear. SVM maps data into higher dimensional space. As a result, making it is simple to separate the data. The use of kernel functions accomplishes it. The recurrent neural network, linear, and gaussian hemispheres are a few of the often used kernels. This study uses linear SVM to categorize preictal and nine-month states.

TABLE II. DLNM NOTATION

Symbol	Explanation
$\Delta W(t+1)$	Revised weight
$\Delta B(t+1)$	Revised bias
L	Layer number
Λ	Regularized parameter
Y	Activation function (sigmoid)
$\sigma(z)$	Activation function (softmax)
f(x)	ReLU

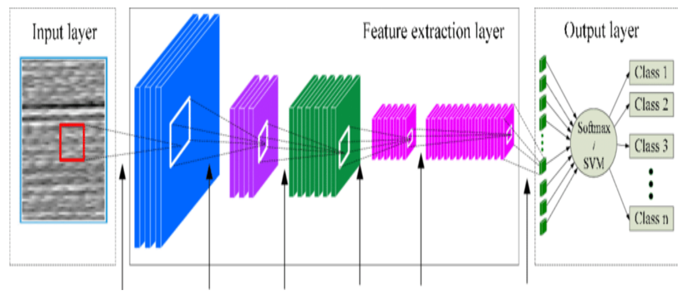

Fig. 3. Proposed DLNM.

IV. RESULTS AND DISCUSSION

We used our suggested technique on 24 CHBMIT scalp EEG dataset individuals to classify interictal and preictal states and predict epileptic episodes. Our average sensibility is 93%, and our specificity is 91%. The strategy we suggest has a 21-minute average anticipation time. The results of our suggested technique are compared to cutting-edge seizure prediction systems. It has been shown that our suggested strategy for anticipating grand mal seizures outperforms prevailing techniques based on specificity and sensitiveness. Preictal class is a college career according to our definition. Hence a 100 % detection rate with few FPR is crucial. These ROC curves assess the effectiveness of approaches by plotting sensibility against a false positive rate. A method's performance is deemed satisfactory if positive result alarms do not rise as sensitivity increases. In terms of attaining real positive rates with few false reports, it is evident that our suggested strategy works better. As a result, it can be said that the suggested strategy accurately predicts seizures in people with Epilepsy. Here, single input is given and multiple class labels based classified outcomes of extracted as output. The outputs are related to the dataset class labels.

The extracted features are provided as the input to the DLNM. The features are identified to enhance the quality of prediction. The effectiveness of the systems is determined by comparing the classification choices made by the classification to the manual choices made with each session through one or more new born EEG specialists. The classifier's conclusion is captured by the binary classification, which has four types: true positives (TP), epochs properly identified as seizures; false positives (FP), epochs wrongly tagged as seizures; true negatives (TN), successfully identified non-seizure epochs; and false negatives (FN).

Accuracy (Acc): It is the number of occurrences accurately identified. The formulae given below are to determine accuracy:

$$Accuracy = \frac{TP+TN}{(TP+FN+TN+FP)} \quad (6)$$

Precision (Pn): It is calculated as the ratio of accurately forecasted to total positive observations.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall (Rc): The percentage of total useful content that the good stuff identifies is known as recall.

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

Sensitivity (Sn): Sensitivities is the only positive metric considering all situations.

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad (9)$$

Specificity (Sp): It measures the number of correctly detected true negatives and is computed as follows:

$$Specificity = \frac{TN}{TN+FP} *100 \quad (10)$$

F-measure: It is a harmonic average of memory and accuracy. The highest possible F grade is 1, which denotes faultless accuracy and recall.

$$F - measure = \frac{2*recall*precision}{recall+precision} \quad (11)$$

Table III depicts the comparison of the anticipated DLNM with other approaches for error computation, i.e. MAE and RMSE along with execution time. The MAE value DLNM model is 3.2 which is lesser than SVM, RF, k-NN, NB and MLP (see Table III) and the RMSE of the anticipated DLNM is 11.2 which is lesser than SVM, RF, k-NN, NB and MLP. The execution time of DLNM is 0.02 seconds lesser than SVM, RF, k-NN, NB and MLP (see Fig. 4 and Fig. 5).

Fig. 4. Confusion Matrix.

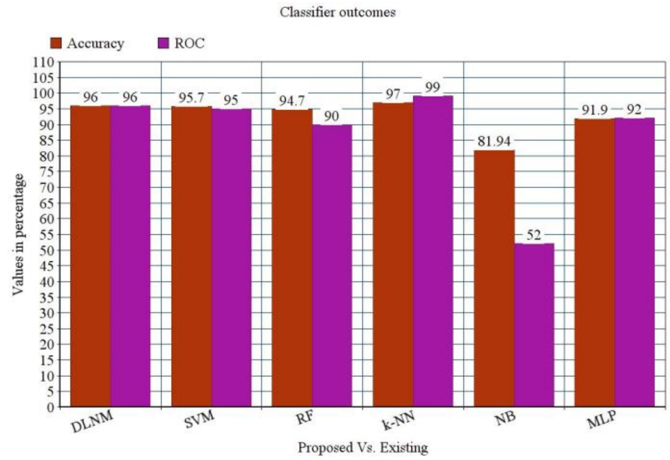

Fig. 5. Accuracy and ROC Comparison.

TABLE III. CLASSIFIER OUTCOMES

Method	Accuracy (%)	ROC	MAE	RMSE	Time (s)
DLNM	96	96	3.2	11.2	0.02
SVM	95.6	95	4.2	20.6	0.30
RF	94.7	90	5.4	22.6	10.36
k-NN	97.0	99	6.67	15.27	17.04
NB	81.9	52	29.64	38.84	3.68
MLP	91.9	92	12.8	25.5	22.05

Table III depicts the comparison of the anticipated DLNM model with various prevailing approaches like SVM, RF, k-NN, NB and MLP. DLNM's accuracy is 96% which is 0.4%, 1.3%, 14.1% and 4.1% higher than SVM, RF, NB and MLP and 1% lesser than k-NN. The recall of the anticipated model is 92% which is 7%, 3%, 5%, 6% and 8% higher than other approaches. DLNM's F-measure is 92% which is 7%, 3%, 5%, 7% and 8% superior to others. The DLNM precision is 92% which is 7%, 3%, 5%, 6% and 8% superior to others (see Fig. 6 and Fig. 7). Based on these analyses, it is proven that the anticipated DLNM model works well compared to other approaches in terms of performance indices.

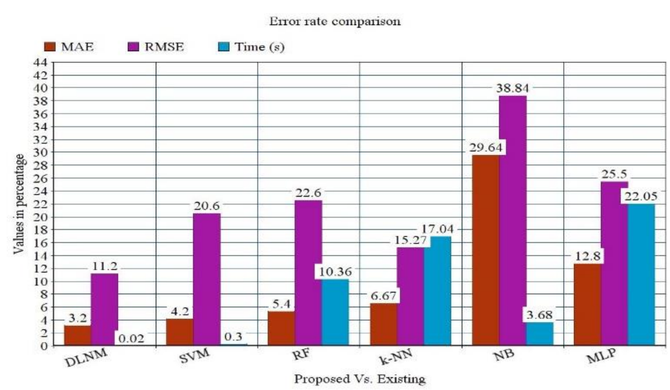

Fig. 6. Error Rate Comparison.

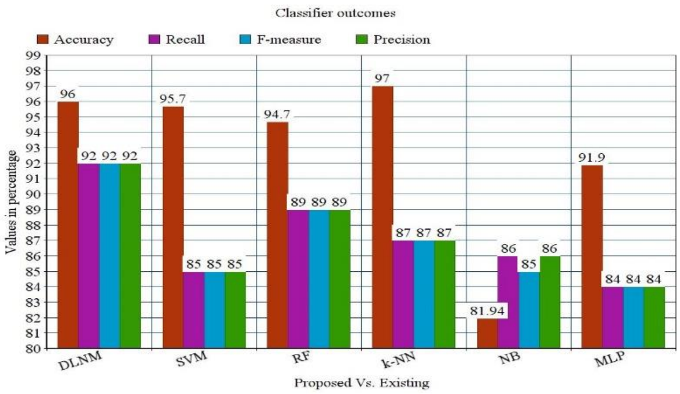

Fig. 7. Performance Metric Outcomes.

V. Conclusion

This work has suggested a technique for predicting epileptic seizures with DL. Individuals with Epilepsy may lead risk-free life when an adequate event prognosis is achieved. The suggested approach combines morphological operations with DLNM and identification using a DL classifier to outperform existing approaches with prediction accuracy. The novelty of identified with the DLNM model is its ability to encourage feature reuse, reduced number of parameters and stronger feature propagation which enhances the prediction outcome. Nevertheless, there is still space for development in several areas if filtering is improved in the future to improve the signal-to-noise ratio. Deep learning algorithms for feature extraction and classifying need several parameters. Future studies may thus be done to lower the number of factors. The suggested approach offers patient-specific seizure prediction, similar to other cutting-edge approaches. Continued studies on non-patient individual epileptic seizure prediction systems are necessary.

VI. Future Research

In the future, this work is extended with multi-modal analysis and the hybrid learning approach is adopted for performing the prediction. The quality of prediction has to be improved further to make faster prediction outcomes.

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