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Feature Fusion of Time-frequency and Deep Learning Features for Epileptic Seizure Detection using EEG Signals

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ABSTRACT- A persistent brain's neurological state is epilepsy, characterised by recurring seizure. Brain electrical activity is measured using EEG signals, which can be used to detect and diagnose significant brain problems such as Epilepsy, Autism, Alzheimer's etc. However, manual EEG data processing is time-consuming, requires highly skilled clinicians, and is associated with low inter-rater reliability (IRA). A computer-aided diagnosis approach for epileptic seizure detection from multichannel EEG recordings by fusing the time-frequency features and the deep learning features extracted from Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) model using canonical correlation analysis (CCA) method is provided in this study. Deep Learning features are extracted using CNN-GRU layers, motivated by recent advancements in image classification and optimised for use with EEG data. We have also extracted time-frequency features such as spectral entropies and Sub Band energies from Empirical mode decomposition (EMD) and Hilbert Marginal Spectrum (HMS). We used CHBMIT dataset to carry out the results and showed that the method proposed for fusing the time-frequency features and deep learning has given better performance.

Keywords: EEG; Epilepsy; Feature Fusion; EMD; HMS; CNN-GRU.

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1. INTRODUCTION

Brain functions as the most essential operational organ in our body, controlling and coordinating the other muscles and nerves. Some brain disorders like autism, sleeping disorders, epilepsy etc. are sensitive to certain frequencies of brain impulses. Brain waves in *table 1*, displays states associated with various signals and linked brain areas [1]. Epilepsy is considered one of the most prevalent non-contagious brain illnesses. Epilepsy has been identified in approximately 1% of people worldwide. Temporary electric disturbances are experienced by patients who have epileptic seizures. One or more strokes occur in a month for about 20–30% of people with epilepsy. Physical injuries during an epileptic seizure period could possibly result in the patient's death. The patients also struggle with social isolation and serious mental illnesses. The International League Against Epilepsy (ILAE) in 2017: has proposed three new classifications of epileptic seizure types and they are focal, generalised, and epilepsy with unidentified symptoms. Each epileptic seizure type, as well as the brain regions experiencing convulsion, are described in this classification along with some precise and in-depth information about them. Early identification of epileptic seizures is critical since it significantly slows the progression of the disease [2].

EEG is a non-invasive method of measuring brain waves that includes recording electrical activity. Electrodes can be placed across human's skull and scalp to measure the brain activities by their electrical potentials. It is often used to diagnose and treat many neurological conditions, including somnipathy, epilepsy, coma etc. Medical professionals frequently use EEG [3], as a diagnostic tool because of its great temporal resolution and low cost, despite the fact that it has less spatial resolution than methods of brain imaging like Computed Tomography (CT), functional Magnetic Resonance Imaging (fMRI) scan and others.

Interpreting an EEG signal [4], to find out if someone has a neurological illness often requires long-term surveillance involves the recording of several brief sessions, because symptoms are not always present in the EEG signal. Large volumes of data are produced during this procedure, which require skilled investigators to manually interpret. Due to the scarcity of skilled specialist investigators and the massive volume of data, analysis of EEG is a lengthy procedure that can creates a lag in the patient's course of therapy ranging from hours to weeks. By speeding up the reading process and hence decreasing workload, it might be beneficial to automate EEG interpretation process could be helpful to neurologists. This is why machine learning and deep learning systems that automatically interpret EEG have gained popularity in recent years.

Table 1: Frequencies and properties of brain waves

Brain wave	Frequency (Hz) Range	Behavioural State	Location
Delta (δ)	0 – 4	Deep sleep, dreamless sleep, severe organic brain disease	Thalamic region
Theta (θ)	4 – 7.5	Drowsy state, deeply relaxed	Hippocampus region
Alpha (α)	8 -13	Normal, relaxed	Posterior region
Beta (β)	14-30	Busy, anxious thinking, concentration	Frontal, somatosensory and Parietal
Gamma(γ)	30-100	Intense concentration, during tension	Somatosensory cortex

To detect epileptic seizure with EEG signals, many researchers have developed many automated methods and some of them are reviewed in this section. Pre-processing of EEG signals, significant features extraction, and classification are all part of the automatic seizure identification. Variety of Machine Learning models which are traditional and Deep Learning models using scalp EEG measurements have been proposed. In these approaches, electrodes are placed on patient's scalps to capture EEG.

EEG signals are initially pre-processed to reduce noise and improve Signal to Noise (SNR) ratio. EEG signals can be filtered using bandpass Butterworth and notch filters as standard pre-processing techniques. High SNR(Signal-to-noise) ratio with EEG recordings, we can use common and optimised spatial pattern filter. Empirical mode decomposition is especially beneficial for pre-processing EEG recordings because it yields IMFs (Intrinsic Mode Functions) by preserving low-frequencies, so that we can increase the SNR (Signal-to-Noise Ratio). Fourier and wavelet transformations can also be used as pre-processing steps before being fed into convolutional neural networks [13].

After the noise has been removed, patterns from signals are extracted, and significant features are chosen that have a high variance between different classes and low variance within same class. For the purpose of detecting epileptic seizures, researchers have extracted custom features in the temporal, spectral, and time-frequency domains. Temporal characteristics such as first four Statistical Moments, Estimated Entropy, Hjorth Parameters, and Lyapunov Exponents. Spectral features such as PSD (Power Spectral Density), Spectral Moments are few of those [16-18].

The effectiveness of Deep Learning algorithms over several traditional Machine Learning applications, which include Object Detection, Video Processing, identification of Alzheimer's etc., has garnered a lot of interest. To analyse and learn temporal patterns in EEG signals Recurrent Neural Networks (RNN) are used extensively [24]. Improvements in RNNs that are Long Short-Term Memory (LSTM) [14] and Gated Recurrent Unit (GRU) has greatly outperformed than traditional RNNs. To address vanishing gradient and exploding gradient problem, gates are used in them. Epileptic seizure detection from EEG signals has recently been done using LSTM. We used GRUs in this study, since only few parameters are needed when compared to LSTM, as a result, it offers a shorter training period despite requiring data to generalise. In EEG data processing, Convolutional Neural Networks (CNNs) also gained substantial remark. CNNs can be applied to the wavelet space and raw data to classify epileptic EEG signals, and in other datasets they have done exceptionally well. The capacity of CNNs to automatically learn new features yields greater results when compared with hand-engineered features, if volume of data needed to train the CNNs is sufficient [19-22].

The performance accuracy of epileptic seizure detection models mainly depends on the features extracted from domain knowledge. Manually extracted features (handcrafted) need expert domain knowledge so these have significant importance in seizure detection. Lately deep learning methods are introduced for automatic feature extraction from raw EEG signals data for seizure detection models. However, previous studies stated that the significance of handcrafted features cannot be overlooked as these are extracted with expert domain knowledge. Therefore, the fusion of both the handcrafted and automatically extracted features using CNN-GRU for seizure detection to boost the performance is proposed in this work.

2. SYSTEM MODEL

The CHBMIT dataset, which consists of EEG recordings of pediatric patients with uncontrollable seizures, was gathered at Children's Hospital Boston [5] is used in this work. The recordings, which were collected from 23 individuals, were split up into 24 cases and given the numbers chb01 through chb24. Each case includes 9 to 42 EDF recordings that are between one and four hours long. Table 2, shows the details of dataset. With a 16-bit resolution, sampled signals at a rate of 256 Hz. At least 23 channels are included in each recording. The international 10-20 system is used to determine the placement, names of the EEG electrodes and are analyzed for the seizure or non-seizure.

Table 2: CHB-MIT EEG Dataset

Type	Scalp EEG
Subjects	22
Age	1.5 to 19
Male Subjects	5
Female Subjects	17
Channels	23
Sampling Rate	256 Hz
Seizure files	185 hours
Total EDF Files	682 hours

A method for epileptic seizure detection from multichannel EEG recordings by canonical correlation analysis-based fusion of time-frequency features with deep features. *Figure 1* depicts

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the process flow diagram of proposed feature fusion based epileptic seizure detection. The raw multichannel EEG signals dataset for epileptic seizure detection are collected from Childrens Hospital Boston-Massachusetts Institute of Technology (CHBMIT) for different subjects. Preprocessing of signals can be carried out by common average referencing and bandpass filter to remove Signal to Noise Ratio (SNR) for all 23 channels. The preprocessed signal is decomposed into IMFs using EMD and from IMFs the Hilbert Marginal Spectrum is generated using Hilbert-Haung Transform (HHT). Sub-band energies for brain frequency rhythms, Shannon entropy, Tsallis entropy, and Renyi entropy, the time-frequency features are extracted from the Hilbert Marginal Spectrum which is a time-frequency transformation of EEG signal. Deep learning features are extracted using CNN-GRU layers. Feature fusion of time-frequency features and features extracted from CNN-GRU using canonical correlation analysis (CCA). Softmax classifier receives the combined features as input and will classify as seizure and non-seizure events. Accuracy, Precision, Recall and F-measures are the performance metrics that are used to acess the performance of the model.

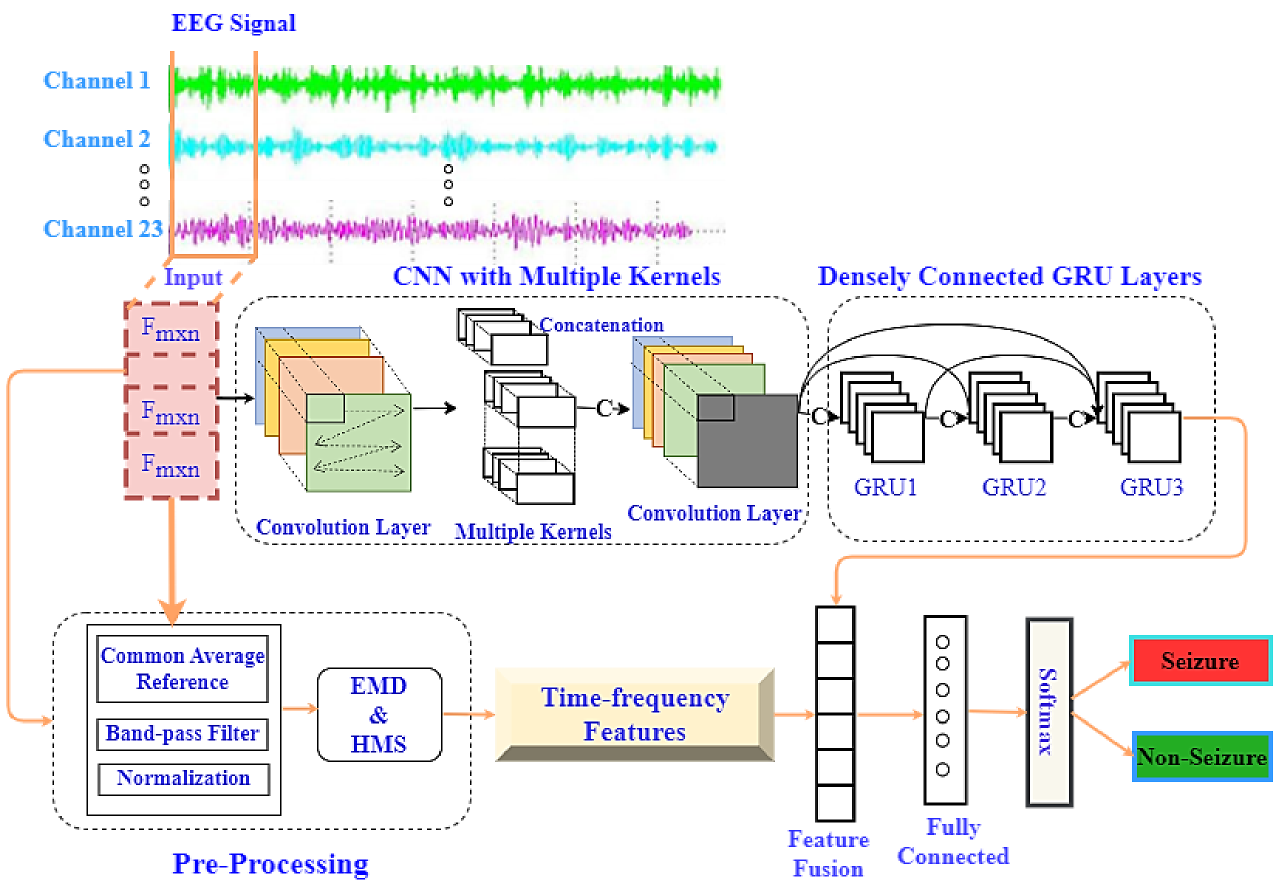

Figure 1: Process Flow Diagram of Proposed Feature Fusion Based Epileptic Seizure Detection

Due to improper electrode placement, patient eye blinking, and muscle movement. Pre-processing of EEG signals is necessary for further implementations, EEG signals are segmented into epochs, which are brief intervals of time. The signals are filtered up to cut-off frequency of 45 Hz using a Butterworth filter. Using 2sec epochs with short durations produces more seizure epochs to train the model of CNN-GRU. Each 2-sec epoch is decomposed into 6 IMFs using EMD. EMD (Empirical Mode Decomposition) and Hilbert marginal spectral analysis are the two parts of the HHT (Hilbert Huang Transform) [7]. EMD's signal decomposition approach is straightforward, direct, and adaptable.

2.1 Empirical Mode Decomposition

EMD is used to divide signal into meaningful components and to gain new insight into features. It is an adaptive basis system to determine physically meaningful modes from data. The EMD [6] is a common method for decomposing nonlinear, non-stationary signals that decomposes into sum of Intrinsic Mode Functions (IMFs) which are amplitude and frequency modulated signals.

2.2 Hilbert Marginal Spectrum

All IMF extracted from the preprocessed signals using EMD, can further analyzed using HHT. Hilbert-Huang transform describes the imaginary portion of the function to make it an analytic function also called as progressive function, in which every frequency component below *zero* will be set as *zero*, in order to preserve the imaginary part of signal, during inverse transform. The Hilbert transform yields instantaneous frequencies that are functions of time when applied to singular vectors. This gives a distribution of energy over time and

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frequency. To simplify the idea of instantaneous frequency and time, it can represent time-frequency localization.

2.3 Time-frequency features

Various spectral entropies and sub-band energy of different frequency bands are time-frequency features used in this paper are given below.

2.3.1 Spectral entropies

Entropy is a measure of dysfunction of physical systems. It is associated with the amount of knowledge that can be learned through observing chaotic methods [15]. It is a practical approach for determining the spectral power distribution. A probability distribution that is broad and flat produces a high entropy, whereas low entropy results from a narrow, peaked distribution. Numerous fields have effectively used and investigated the Fourier spectrum-based entropies. Entropy is a statistical term used to describe the variability within an EEG signal [10]. The HMS-based entropy may perform well in the classification of EEG signals because HMS has outstanding nonstationary signal processing properties. The Shannon, Renyi, and Tsallis spectral entropies [11-12] are described in this study.

2.3.2 Sub-Band energy

Energy characteristics plays a key role in detecting epileptic seizure episodes. The energy characteristics are derived from frequency ranges of the brain waves (delta: 0-4 Hz; theta: 4-8 Hz; alpha: 8-12 Hz; beta: 12-30 Hz; gamma: 30-50 Hz) from EEG signals. Seizure and non-seizure signals have vastly different patterns of energy distribution. The delta wave makes up most of the energy in a typical EEG signal, however in a seizure, the delta wave only makes up a small part of the total energy. To classify EEG signals, sub-band energy is a distinctive feature. The magnitude of the squared spectrum components is added to determine the sub-band energy.

2.4 Deep Learning Features

CNN-GRU was motivated by recent advances in image processing and is designed to efficiently work with EEG data. In this work, Deep learning features are extracted using CNN-GRU layers. From the standard CNN model, combined CNN-GRU model is proposed to further improve performance in terms of accuracy and time. It is built by stacking three conv1D layers and three deep Gated Recurrent Unit (GRU) layers. The architecture of single conv1D block and followed by densely connected GRU layers proposed in this work. CNN-GRU can combine information from several time scales and extract features from mulpile filters.

In this work, every Conv1D layer has multiple filters of different sizes, followed by denesely connected GRU layers. For each conv1D layer the optimal filter size can be determined by multiple filter lengths. The vanishing and exploding gradients problem is addressed by the GRU layers that are densely interconnected. As a result, it might be possible to develop more sophisticated CNN-GRU variations for harder problems. Furthermore, in the GRU layers, dense connections provide feature reuse and propagation [9].

2.4.1 CNN with multiple filters

The inception module [23, 25], in contrast to conventional convolutional neural networks, employs filters of varying sizes in a convolution layer to collect characteristics at various degrees of abstraction. The network can effectively extract pertinent features by collecting and processing visual data at various scales. In this work, three conv1D layers of 32 filters are used, each conv1D has three filters with sizes 2×2, 4×4, and 8×8. A max pooling operation is performed parallelly with a size of 3×3.

2.4.2 Gated Recurrent Unit

A gated recurrent unit (GRU) derives the current value of the hidden state, denoted by h_t provided in *equation (1)*, by linearly interpolating between the prior value, denoted by h_{t-1} and an intermediate candidate hidden state $\tilde{h}_t$ calculated using *equation (2).* Update gate z_t and reset ate r_t are the two gates being used by GRU. The amount of data from earlier time steps that must be carried forward is calculated by the update gate z_t denoted in *equation (3).* The reset gate r_t denoted in *equation (4)*, regulates how much information from the past must be forgotten. The current memory is computed using the reset gate to store relevant information from the past. At the final stage, h_t vector is calculated such that it transfers current unit data to the network. Formally, the GRU can be expressed mathematically as follows:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{1}$$

$$\tilde{h}_t = g(W_h \cdot x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{2}$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{3}$$

$$r_t = \sigma(W_z x_t + U_r h_{t-1} + b_r) \tag{4}$$

Where $\odot$ denotes element-wise multiplication, g and σ represents nonlinear activation functions, h_t represents hidden state, h_{t-1} is previous value of hidden state, z_t denotes update gate, r_t denotes reset gate and W_h represents weights of hidden state.

In this work, three conv1D layers with three filters, followed by densely connected GRU layers.

2.5 Feature Fusion of Features using CCA

CCA is an algorithm for unsupervised learning. To increase the correlation between the projections, it projects the input data to a lower dimensional common subspace [8]. The correlation between the combined variables is maximized by finding a linear combination of two variables. The feature-level fusion performed by CCA is based on linear mixing that maximizes the inter-subject covariations of the features of the two modalities. Covariance is used to assess the correlation between the two modalities. Although it is believed that the converted variates will have the highest correlation possible between two feature vectors, unrelated to one another. Given that it is invariant to a variety of measurement units, modulation schemes, and data kinds, the CCA linear combination model is regarded as adaptable. In this work, CCA is used to fuse the deep learning features and time-frequency features for finding correlation between features.

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3. RESULTS

For epilepsy seizure detection experiments are conducted using python programming language. EEG segmentation and noise removal are implemented using MNE package, EMD and HSA are implemented with EMD package, CNN and GRU implementation was accomplished utilizing the Google Colab Pro environment, Keras 2.0, and Tensor flow 1.4.0.

3.1 Dataset

In this work, a publicly available CHBMIT dataset was used. Sample raw seizure multi-channel EEG signals are shown in *figure 2* and non-seizure multi-channel EEG signals are shown in *figure 3*. In the above said figures, x-axis represents time and y-axis represents number of channels. Based on the annotations available in the dataset, data is labelled as seizure and non-seizure classes.

Initially the scalp EEG data were pre-processed by applying a common average referencing, fourth order zero phase band-pass Butterworth filter between 1 Hz and 45 Hz. With short epochs we can try to reduce the outcome of EEG signal being non-stationary so the pre-processed EEG signal segmented into 2sec segments for 23 channels, resulted in 239 seizure segments for 182 minutes, 240 non-seizure segments for 184 minutes. The experiments carried out with a training data of 70% and testing data of 30% from the total 479 segments or epochs.

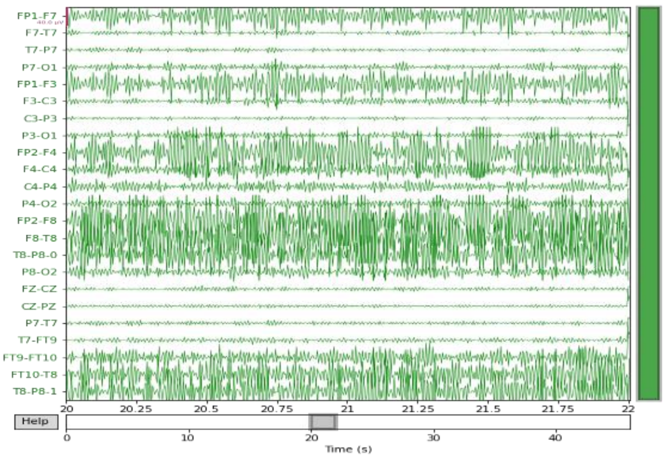

Figure 2: Sample seizure EEG Signal with multiple channels

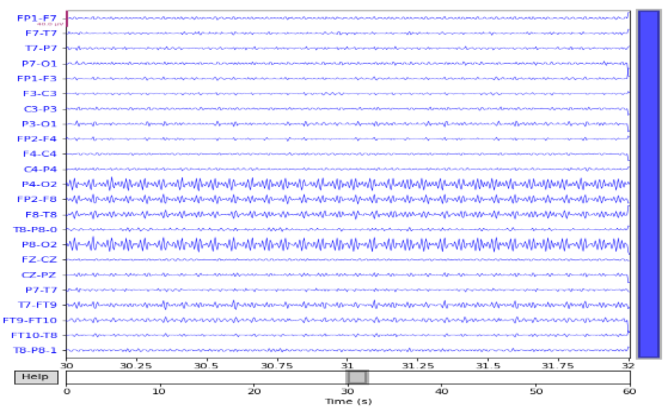

Figure 3: Sample non-seizure EEG Signal with multiple channels

3.2 Performance Metrics

For the assessing the performance and for comparative analysis of the feature fusion technique, various performance metrics are used. Precision, Recall, F-Measure and Accuracy are employed in our proposed work, and they are represented in *equation (5), (6), (7) and (8)* respectively. The *figure 4*, shows the Confusion Matrix also known as a contingency table for seizure and non-seizure classes of epilepsy seizure detection.

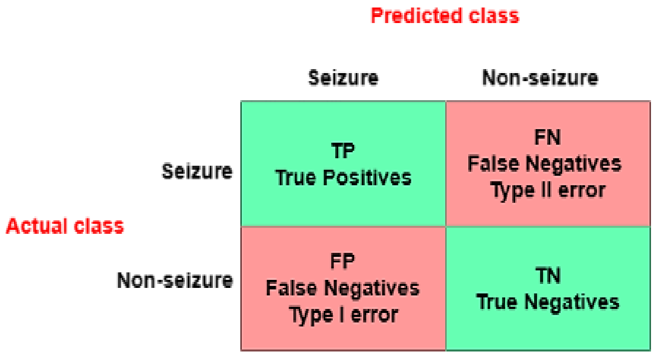

Figure 4: Confusion Matrix for Seizure and Non-seizure classification

For prediction, the elements of Confusion Matrix, i.e., True Positive (TP) indicates correctly predicted seizure class, True Negative (TN) indicates correctly predicted non-seizure class, False Positive (FP) indicates incorrectly predicted non-seizure class, False Negative (FN) incorrectly predicted seizure class values are used to compare the labels of actual class and predicted class.

Precision: Precision is defined as the ratio of accurately predicted seizure class to all actual seizure and false seizure class in a binary classification problem.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

Recall: Recall is the ratio of accurately predicted seizure class to all actual seizure and false nonseizure class in a binary classification problem.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

F-Measure: As Precision and Recall have a harmonic mean; it is necessary to tune the system for either Precision or Recall, as these factors have a greater impact on the end output.

$$\text{F-Measure} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{7}$$

The F-Measure is derived for seizure and non-seizure values in the same way as Precision and Recall are obtained for seizure and non-seizure classes.

Accuracy: It is the most widely used metric for determining classification Accuracy. The ratio of correctly classified classes to the total number of classes.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{8}$$

3.4 Feature Extraction

The time-frequency features extracted using shannon entropy, tsallis entropy, renyi entropy and sub-band energy of seizure signals. A total of 184 features are extracted which includes 23 Shannon entropy features, 23 Renyi entropy features and 23 Tsallis entropy features, for all 23 channels for single EEG segment. 115 (5 sub bands x 23 channels) sub-band energy feature values extracted from five sub-band rhythms of brain single EEG segment. The time-frequency features values of seizure and non-seizure signals are given in *table 3* and *table 4.*

From *table 3* and *table 4*, seizure signals sub-band energy and entropy feature values are more when compared to non-seizure feature values because of lower frequency flatness. we can observe that sub-band energy of seizure signal is more when compared to non-seizure signal sub-band energy.

Table 3: Entropy Features and Sub-Band Energy Features of Seizure Signal for 23 Channels

Channel no	Shannon Entropy	Renyi Entropy	Tsallis Entropy	Sub-band energy				
				Delta	Theta	Alpha	Beta	gamma
1	4.01	2.34	1.25	0.0824	0.0671	0.0571	0.0478	0.0622
2	5.39	1.12	1.16	0.0863	0.0661	0.0506	0.0436	0.0387
3	6.23	3.45	0.89	0.0841	0.0644	0.0512	0.0426	0.0385
4	5.71	2.01	1.57	0.0856	0.0593	0.0531	0.0476	0.0485
5	5.92	3.45	0.89	0.0849	0.0647	0.0561	0.0443	0.0526
6	4.72	4.02	1.31	0.0896	0.0634	0.0512	0.0471	0.0637
7	5.13	4.12	1.23	0.0929	0.0644	0.0524	0.0482	0.0492
8	5.89	2.89	1.66	0.0861	0.0655	0.0511	0.0534	0.0605
9	6.56	3.12	1.05	0.0913	0.0655	0.0556	0.0428	0.0396
10	4.95	2.65	0.56	0.0891	0.0626	0.0537	0.0437	0.0389
11	5.45	3.22	1.78	0.0921	0.0655	0.0536	0.0473	0.0564
12	5.69	4.35	0.23	0.0849	0.0634	0.0535	0.0441	0.0363
13	4.61	3.87	0.34	0.0862	0.0642	0.0513	0.0434	0.0372
14	5.82	3.28	0.25	0.0838	0.0661	0.0502	0.0594	0.0634
15	4.38	4.55	0.22	0.0809	0.0662	0.0551	0.0431	0.0393
16	4.21	3.67	1.21	0.0869	0.0645	0.0501	0.0542	0.0532
17	4.45	2.62	0.44	0.0821	0.0644	0.0562	0.0486	0.0374
18	5.39	1.15	0.87	0.0915	0.0675	0.0523	0.0445	0.0379
19	5.09	3.45	1.32	0.0834	0.0642	0.0516	0.0423	0.0392
20	6.02	2.65	0.21	0.0844	0.0650	0.0502	0.0912	0.0694
21	4.81	3.21	1.34	0.0836	0.0622	0.0497	0.0801	0.0931
22	4.85	2.12	1.25	0.0867	0.0677	0.0503	0.0488	0.0548
23	5.44	4.32	1.11	0.0809	0.0662	0.0551	0.0432	0.0393

3.4.1 CNN-GRU Parameters

CNN with multiple filters of EEG time series data features is extracted from CHBMIT input dataset for each 2sec epochs of 23 channels and fed into GRU that is considered as optimal and identified to have improved sequence learning abilities. After extracting the spatial features from CNN are provided as input to three GRU layers to extract temporal features. In conv1D blocks ReLu activation function and in GRU layers Tanh activation function is used. These features are trained with three dense layers and in the last layer softmax activation function is applied to classify seizure and non-seizure classes. The Root Mean Square Propagation (RMSprop), Adam and sigmoid optimizer that is known to adapt the learning rate for each of the parameters.

The input has EEG time series data as of size 512 for 23 channels. It is fed into three conv1D blocks with each three conv1D layers having 32 filters of size two, four and 8 respectively. Operation max pooling is performed parallelly

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with size of two. In first conv1D block, after concatenation of all the filters and produces 96 feature vectors with size of 256. It is the input to second conv1D block, after concatenation of all the filters it produces 96 feature vectors with size of 128 which is passed as an input to the third conv1D block. The third conv1D block produces 96 feature vectors of size 64 after concatenation of all the filters. This sequence of 2048 extracted features becomes input to the GRU part of the network. After passing through the GRU layers it produces the output of 736 features. The parameters of the CNN-GRU model are indicated in *figure 5*.

Table 4: Entropy Features and Sub-Band Energy Features of Non-Seizure Signal for 23 Channels

Channel no	Shannon Entropy	Renyi Entropy	Tsallis Entropy	Sub-band energy				
				Delta	Theta	Alpha	Beta	gamma
1	4.11	1.23	1.11	0.0231	0.0321	0.0262	0.0286	0.0374
2	3.04	2.34	1.25	0.0314	0.0311	0.0206	0.0236	0.0187
3	5.12	1.89	0.21	0.0412	0.0299	0.0312	0.0226	0.0185
4	6.34	3.07	0.65	0.0355	0.0312	0.0231	0.0276	0.0285
5	3.88	2.45	0.25	0.0322	0.0356	0.0261	0.0143	0.0226
6	2.11	1.67	0.24	0.0136	0.0312	0.0312	0.0271	0.0337
7	6.01	1.99	0.67	0.0134	0.0333	0.0224	0.0282	0.0292
8	5.34	1.28	1.23	0.0452	0.0387	0.0311	0.0334	0.0305
9	3.89	2.09	0.45	0.0361	0.0309	0.0256	0.0128	0.0196
10	2.67	2.45	0.62	0.0098	0.0398	0.0237	0.0237	0.0189
11	3.77	2.13	1.11	0.0082	0.0354	0.0336	0.0273	0.0364
12	3.99	1.32	0.87	0.0322	0.0362	0.0335	0.0144	0.0136
13	4.56	2.11	2.01	0.0131	0.0432	0.0313	0.0234	0.0172
14	4.67	2.16	0.39	0.0137	0.0331	0.0302	0.0394	0.0334
15	2.45	1.89	0.87	0.0459	0.0345	0.0355	0.0143	0.0193
16	3.56	1.45	1.87	0.0321	0.0387	0.0201	0.0154	0.0253
17	1.24	1.35	0.38	0.0235	0.0322	0.0262	0.0286	0.0174
18	5.67	2.67	0.46	0.0313	0.0335	0.0223	0.0245	0.0179
19	3.45	2.88	0.52	0.0131	0.0321	0.0316	0.0223	0.0192
20	2.65	1.35	1.05	0.0815	0.0339	0.0202	0.0191	0.0194
21	1.67	1.23	0.21	0.0711	0.0311	0.0297	0.0401	0.0431
22	1.89	1.11	0.28	0.0212	0.0325	0.0203	0.0288	0.0248
23	2.44	1.99	1.53	0.0226	0.0331	0.0355	0.0243	0.0193

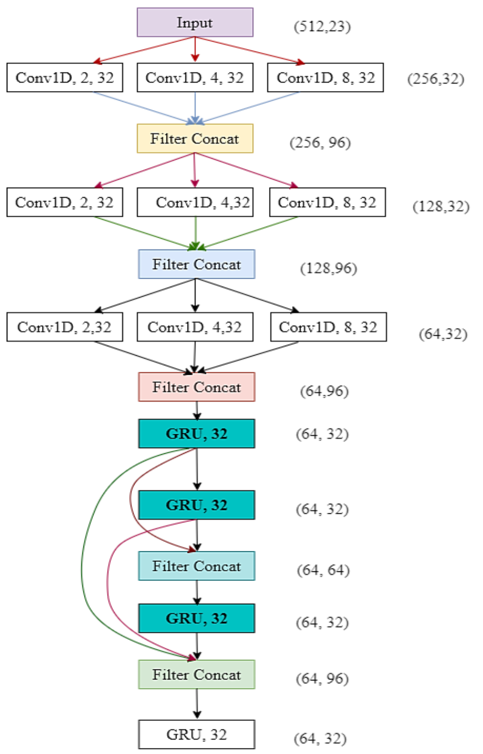

Figure 5. Parameters of CNN-GRU

3.5 Feature Fusion of Time-Frequency Features and Deep Learning Features for Epileptic Seizure Detection

Time-frequency features extracted for single EEG segment of 23 channels is 184 and 736 deep learning features extracted, a total of 920 features are fused using CCA to find correlation between the features.

After CCA, the features are reduced to 628 and these feature vectors are fed to a shallow neural network using two fully connected layers with a sigmoid activation function and a softmax activation function for the output layer to classify into seizure and non-seizure classes.

Table 5 shows the confusion matrix and performance metrics of feature fusion model for analysis of EEG signals to detect seizure and non-seizure classes using different optimizers.

The experiments carried out with a training data of 70% and testing data of 30% from the total 479 epochs. The performance of feature fusion model using RMSProp optimizer in terms of accuracy is 95.14 %.

Table 5: Performance Metrics of feature fusion model for epilepsy seizure detection with different optimizers

Optimizer	Confusion Matrix			Performance Metrics in (%)			
		Seizure	Non-Seizure	Precision	Recall	F-Measure	Accuracy
Adam	Seizure	94.67	5.33	94.67	94.67	94.67	94.44
	Non-Seizure	5.80	94.20	94.20	94.20	94.20	
RMSprop	Seizure	92.65	7.35	92.65	96.92	94.74	**95.14**
	Non-Seizure	2.63	97.37	97.37	93.67	95.48	
SGD	Seizure	89.23	10.77	89.23	92.06	90.63	91.67
	Non-Seizure	6.33	93.67	93.67	91.36	92.50	

Optimizers are algorithms that adjust the characteristics of a neural network, such as weights and learning rate, to reduce losses. When analysed with different optimizers for feature fusion model, the experimental results show that RMSProp optimizer because of convergence speed and stability of the model training process, proved to achieve a highest accuracy of 95.14% when compared to others. *Figure 6* shows the comparative analysis of feature fusion model with different optimizers for EEG signal analysis to classify seizure and non-seizure.

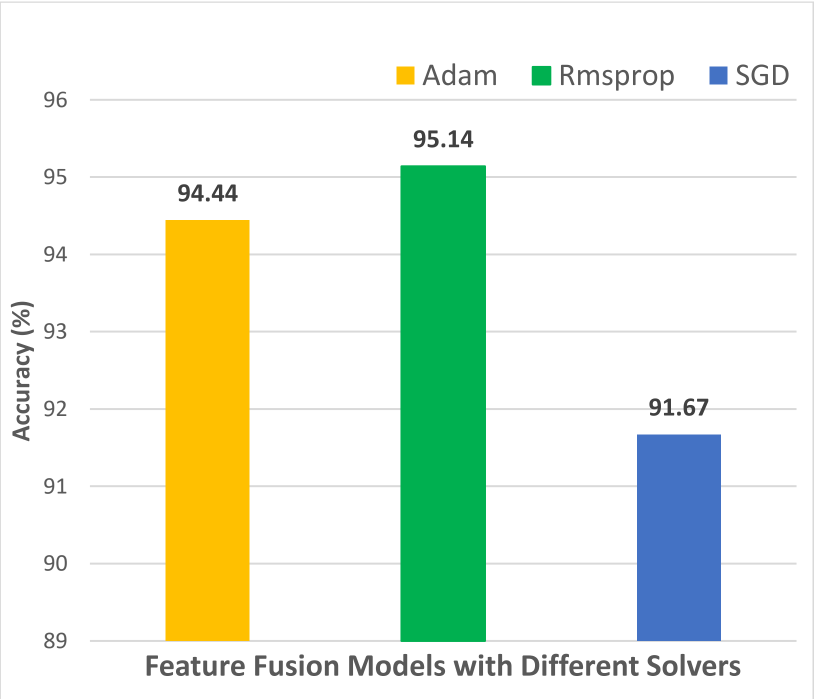

Figure 6: Feature fusion model with different optimizers

In the *figure 7 (a)* shows plot of accuracy of the model over the training and testing data and *(b)* shows plot of loss of the model over the training and testing data. The training accuracy increases linearly over time, until it reaches 100%, whereas the testing accuracy stalls at 90-94% for adam optimizer. The testing loss reaches its minimum only after 20 epochs.

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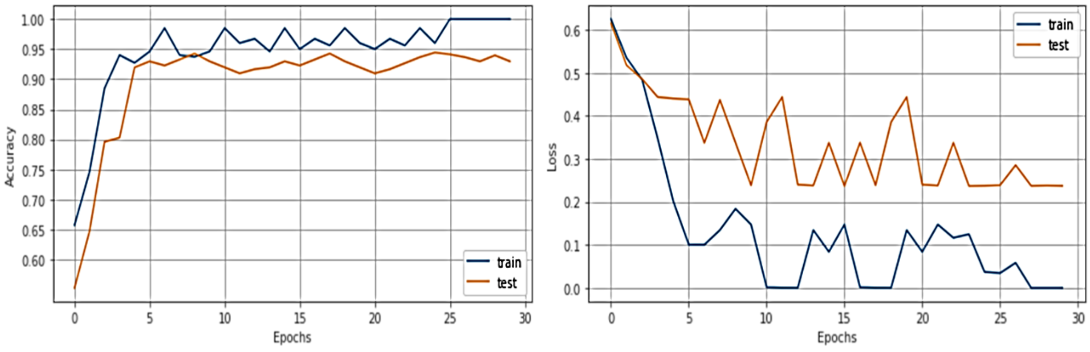
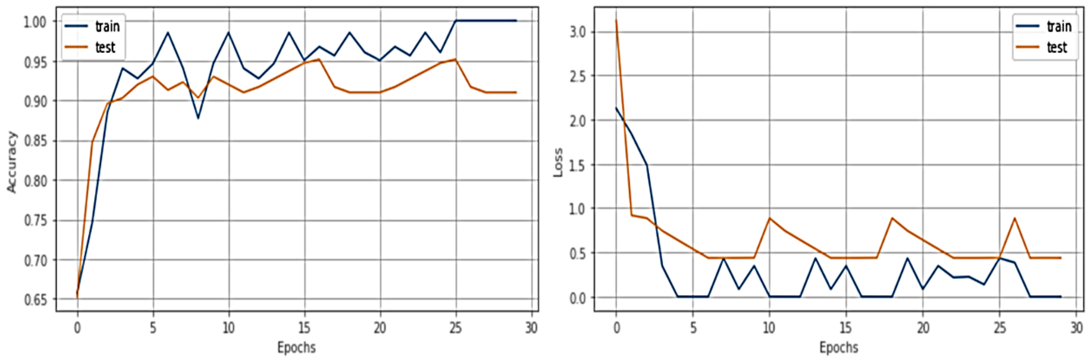


(a) **(b)**

Figure 7. Feature Fusion Model with Adam Optimizer(a) Training - Testing Accuracy and (b)Training - Testing loss

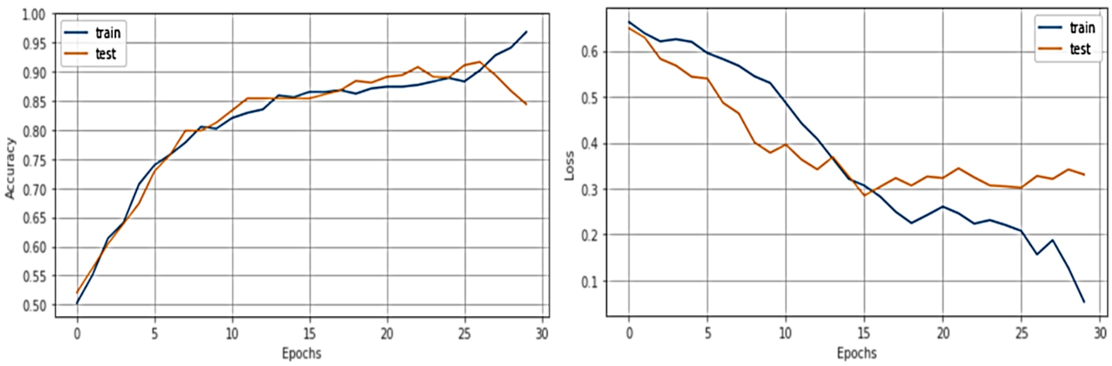
In the *figure 8(a)* shows plot of accuracy of the model over the training and testing data for RMSProp optimizer and *(b)* shows plot of loss of the model over the training and testing data for RMSProp optimizer. The training accuracy increases linearly over time, until it reaches 100%, whereas the testing accuracy stalls at 90-95% for RMSProp optimizer. The testing loss reaches its minimum only after 25 epochs.



(a) **(b)**

Figure 8: Feature Fusion Model with RMSProp Optimizer (a) Training - Testing Accuracy and (b)Training - Testing loss

In the *figure 9(a)* shows plot of accuracy of the model over the training and testing data for SGD optimizer and *(b)* shows plot of loss of the model over the training and testing data for SGD optimizer. The training accuracy increases linearly over time, until it reaches 100%, whereas the testing accuracy stalls at 85-90 for SGD optimizer. The testing loss reaches its minimum only after 25 epochs.



(a) **(b)**

Figure 9: Feature Fusion Model with SGD Optimizer (a) Training - Testing Accuracy and (b)Training - Testing loss

4. DISCUSSION

In *table 6*, the Accuracy values obtained using the proposed approach and compared the results using other approaches described in the literature using the CHBMIT dataset. The table shows that the proposed feature fusion approach outperforms the results obtained by authors of various articles in the literature.

Table 6: Comparative Results Obtained from baseline approaches and proposed approaches in terms of Accuracy

Author-Year	Methodology	Metrics (Accuracy)
Roy (2019)	C-RNN +softmax	83.58
Yuan (2021)	1D CNN-LSTM+ Sigmoid	89.73
Proposed approach	CNN-GRU + Time frequency features +Softmax	95.14

5. CONCLUSION

This work proposes a unique deep fusion method for epileptic seizure detection using EEG signal data. The experimental results demonstrate the feature fusion model delivers better results for Seizure detection when compared to models. A novel CNN-GRU, architecture that is adaptable and flexible, that is useful in analysis of time-series data like EEG is proposed for deep learning feature extraction. Time- frequency features are extracted using HMS, which is well suited method for non-linear EEG signal data. These time-frequency features and CNN-GRU features are fused for improving the efficiency. Time frequency features and Deep Learning features are fused using CCA resulted in 95.14% accuracy.

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