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$\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et: A Novel Multi-Class Epileptic Seizure Classification Model

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Abstract

Epilepsy is a neurological disorder characterized by recurrent seizures, which can affect individuals of all age groups, but infants and older individuals are particularly vulnerable. Sudden epileptic attacks can pose significant risks and be life-threatening, impacting the overall quality of life of affected individuals. With the progress made in medical science, Electroencephalography (EEG) has emerged as a valuable tool for diagnosing and predicting seizure occurrences. The availability of wearable EEG devices, including caps and helmets, has become increasingly prominent in the market. As a result, there has been a recent surge in the development of deep learning-based systems. These systems are helpful for diagnosis in hospital settings and for mobile applications that provide timely warnings and predictions regarding seizure onset. Most of the existing state-of-the-art (SOTA) approaches focus on distinguishing between healthy and epileptic patients. Some studies categorize individuals into three classes: healthy, experiencing the onset of a seizure, or currently having a seizure, specifically focusing on mobile applications. However, limited literature is available on the five-class problem, which is valuable for localization and diagnosis in hospitals and mobile applications. In this regard, we propose our novel model, named $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et, and conduct extensive experiments on a real-world dataset to demonstrate its efficacy in all modes of classification. $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et results in a significant increase of 4% in accuracy in five-class classification.

Keywords: Epilepsy, Electroencephalogram (EEG), Deep learning, Seizure, Diagnosis, Concatenation network, Five-mode classification.

1 Introduction

Seizures are sudden and unexpected transient changes in the brain's electrical functioning, resulting in various physical and mental manifestations. These can arise from a multitude of factors, including epilepsy, head injuries, brain infections, strokes, genetic disorders, or other underlying medical conditions. During seizure, individuals may experience convulsions (involuntary muscle movements), loss of consciousness, sensory changes (such as tingling or strange taste or smell), as well as emotional or cognitive changes (memory loss, mood swings, or hallucinations). Seizure episodes can exhibit considerable variation in duration and intensity. Some episodes may be brief, lasting only a few seconds or minutes, while others can persist for several minutes or even longer. The aftermath of seizure also entails a recovery period characterized by fatigue, confusion, headaches, or muscle soreness ([4]).

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It is essential to emphasize that epilepsy is not the sole cause of all seizures. Recurring and unprovoked seizures characterize epileptic seizures. Epilepsy, derived from the Greek term "Epilepsia", is a neurological disorder, often without a clear underlying cause, and affects 1% of the world's population. While epilepsy can affect individuals of all ages, it is more commonly diagnosed in infants and older individuals. Small children can sustain injuries from sudden epileptic seizures while engaging in physical activities such as playing games, swimming, and cycling. Similarly, elderly individuals, who are more fragile and vulnerable, face the risk of life-threatening accidents resulting from sudden epileptic attacks. Therefore, timely prediction and alarming of the onset of an epileptic seizure can be a blessing in disguise.

Electroencephalography (EEG) can serve as an effective tool for diagnosing and predicting epileptic seizures. The term electroencephalography originates from the Greek word encephalos, which translates to - what is inside the head. In the late 19th century, scalp electrodes were utilized to detect electrical signals in the brain. As technology has progressed over the years, there have been gradual advancements, resulting in the discovery of wearable EEG devices for the wrist and chest. Notably, Sogamoso et al. [30] have further reduced electrode weight by employing graphene-based material. Additionally, wearable caps and EEG headsets that can transmit captured signals to Android devices via Bluetooth technology have been developed ([28, 19]).

While abundant literature is available on the binary classification of EEG data into healthy and epileptic patients ([22, 31, 34]), recent research has focused on developing mobile-based alarming and safety applications that notify individuals about the onset of seizures ([10, 9, 44]). These applications utilize machine learning models to classify EEG signals into healthy conditions before the beginning of seizure and signals during seizure. However, for improved diagnosis and localization of the affected regions of the brain, there is a need to classify EEG signals into five distinct classes (as discussed in Section 3.1). Unfortunately, this research direction has received limited attention due to the complexity and difficulty of distinguishing between the different classes within an EEG signal ([10, 9, 15]). The primary objective of this work is to propose an efficient model that addresses the concern of solving different types of classification problems in epileptic research and can be seamlessly integrated into different mobile and web applications to provide highly efficient seizure prediction systems, contributing to world-class advancements in this field. To this, **contributions** of our work are summarized below.

- We propose a novel neural architecture which we call, $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et for EEG signal classification.
- $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et outperforms existing state-of-the-art (SOTA) methods in five-class problem achieving a significant improvement of 4% in accuracy.
- The proposed model also outperforms existing SOTA methods in ternary classification tasks.
- In binary classification problem, $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et exhibits comparable training performance to SOTA techniques but surpasses SOTA by 3% in test accuracy.
- The model shows lower susceptibility (robustness) to hyper-parameter tuning, including parameters such as the learning rate.

Roadmap: The remainder of the paper organizes as follows. Section 2 reviews existing literature. Section 3 describes the data considered for current research analysis and methodology of the proposed concatenation network $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et. Section 4 validates the efficacy of $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et against SOTA methods. Section 6 concludes the work.

2 Related Work

Epilepsy seizure prediction has been the subject of intense research and development in recent years ([23, 25]). The quest for reliable and efficient methods in epilepsy seizure prediction has led to a multitude of research endeavours, encompassing various domains such as wave analysis, computer-aided diagnostics, and machine learning-based models ([26]).

The work in [22] utilizes machine learning techniques, including multi-layer perceptron (MLP), principal component analysis (PCA) with random forests, linear discriminant analysis, and PCA with artificial neural network (ANN). They demonstrate that the PCA with ANN method outperforms other approaches in the binary classification of healthy versus unhealthy individuals. In a slightly different direction, focusing on binary classification between unhealthy epileptic patients before and during seizures, work in [31] proposes a feature scaling technique fed into a three-layered neural network. [34] carries out similar work using a random forest classifier. Furthermore, [7] pursues a similar approach utilizing deep convolutional networks, Bi-LSTM, and RNN. [44] then further improve upon these methods by employing convolutional neural networks (CNN) on raw signals for binary classification. The authors also explore the ternary problem of classifying signals into healthy individuals, epileptic patients before seizures, and epileptic patients during seizures. The work in [8] proposes an innovative system for accurately classifying epileptic EEG signals using an information-fusion-based approach. The algorithm combines information and determines feature weights based on the information gain ratio. Finally, a probabilistic neural network and the k-nearest neighbour were used for classification. Authors in [20] proposes a ensemble based extreme learning method based on linear discriminant analysis, this proposed feature extraction method significantly outperformed other related state-of-the-art present for classification. Recent work in [37] employs automatic preprocessing method using the idea of a common average reference to remove artefacts from the signals, followed by the application of LSTM for binary classification.

With the advent of wearable devices and the integration of machine learning algorithms, the potential for real-time epilepsy seizure prediction has become increasingly tangible [13], revolutionizing the management of this neurological disorder. Noteworthy work in this direction includes EpilepsyNet, an interpretable self-supervised encoder-decoder model designed for wearable devices, proposed by [14].

Recent advancements in wavelet processing methods, coupled with deep learning, have also been explored in the diagnosis and prediction of epilepsy [27]. Several notable works in this area include [38, 1, 36, 29, 12, 35]

One major limitation of the works mentioned above is that they primarily focus on binary or ternary classification in epilepsy diagnosis and prediction. However, the comprehensive management of epilepsy often requires the localization of epileptic regions to facilitate targeted medication. Consequently, this introduces a five-class classification problem (for more details, refer to Section). Only a few studies have addressed this specific direction. Notable existing works include [9, 10]., who propose EpilNet, a 1D-CNN network that outperforms state-of-the-art (SOTA) methods, and [15]., who utilize an LSTM-based approach. Building upon these contributions, we propose a novel model that performs effectively for the five-class problem and surpasses the SOTA performance in binary and ternary classification. We now next look into the proposed method architecture and methodology.

3 Material and Methodology

3.1 Dataset

The Epileptic Seizure Recognition Dataset (ESRD) is publicly available in the UCI repository, gathered by the Epileptology Department at Bonn University [2]. This dataset consists of five different folders, treated as 5 different classes, and each folder consists of 100 files. Each file is a single individual's brain activity or EEG signal recording. The duration of each EEG signal recording is 23.6 seconds recorded using a 128-channel amplifier at a sampling rate of 173.61 Hertz. Thus, the signal comprises 4097 (23.6×173.61) data points, which are segmented into 23 chunks, each representing 1 second. Consequently, the dataset is structured into 23 data row samples, each with a vector length of 178 signal points. After capturing the signals, they are converted from analogue to digital format using an analogue-to-digital converter.

The motivation to utilize the ESRD dataset is rooted in its inclusion of single-channel EEG data, which is adeptly compatible with small wireless sensors, thereby enhancing the efficiency of EEG data processing [16]. The dataset comprises 11,500 samples, each representing a vector in the space $\mathbb{R}^{178}$, corresponding to the 128 channels of the EEG signals. Additionally, each sample is associated with a class label ranging from A to E, denoted as 5 to 1, respectively. Note that these classes are sometimes referred to as Z, O, N, F, and S due to the naming conventions used in the source folder structure. Figure 1 displays the raw signals (for a duration of 1 second) of different classes, randomly sampled from each class. Class A corresponds to signals from healthy individuals with open eyes, while class B represents signals from healthy individuals with closed eyes. Class C and D contain signals from unhealthy individuals during seizure-free periods, specifically from the hippocampal and epileptogenic regions, respectively. Class E

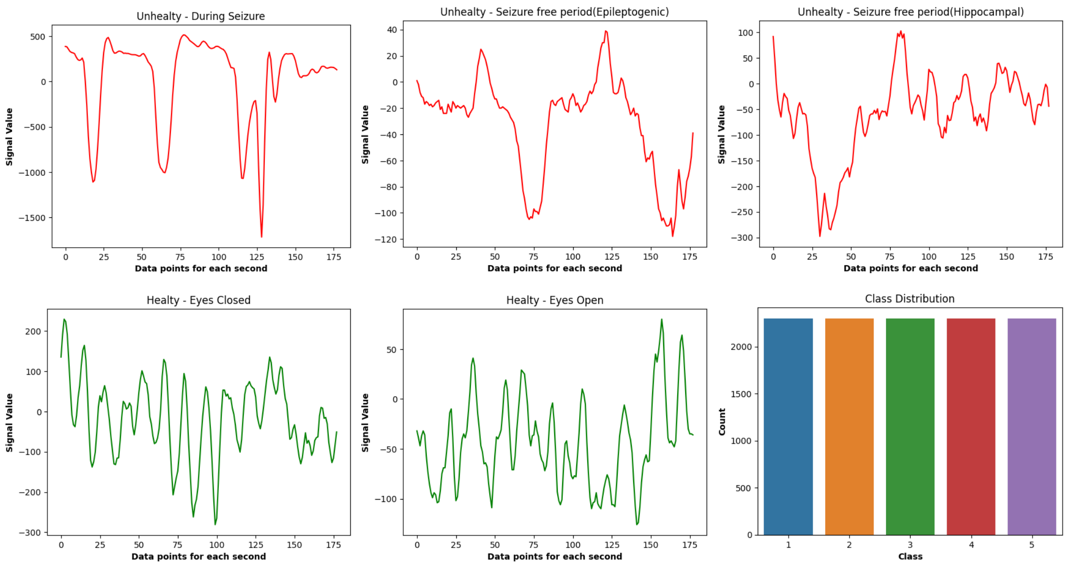

Figure 1: The plot shows the EEG brain signals for the ESRD dataset. The first row showcases random instances of signals from unhealthy individuals, with column 1 representing class 1, column 2 representing class 2, and column 3 representing class 3. The second row includes random instances of signals from healthy brains, with column 1 representing the eyes closed(Patient had their eyes closed while recording the EEG signal) and column 2 representing the eyes open(Patient had their eyes opened while recording the EEG signal). The last column illustrates the dataset distribution for each class in the ESRD dataset [21].

represents signals from an unhealthy individual during an active seizure. Furthermore, Figure 1 also demonstrates the uniform distribution of samples across the different classes, highlighting the balanced nature of the dataset. It is important to note that there are no missing values in the data, making it directly usable for feature extraction and machine learning-based models.

3.2 Pre-processing

The literature on seizure prediction has explored the problem from various perspectives. In certain scenarios, the objective is to determine whether a person is healthy (classes A and B) or an epileptic patient (classes C, D, or E). This distinction becomes particularly important, for example, when admitting individuals to hospitals to confirm if their symptoms are related to epilepsy. We call this as **Task 1**. On the other hand, in applications focusing specifically on the onset of seizure, it is necessary to examine specific subsets formed by grouping classes, namely A, B, C, D, and E. We will discuss **Tasks 2 and 3** in the experimental section later in Section 4.

It is noteworthy that accurately identifying the affected cortical region is crucial for effectively managing and preventing future seizures. This requirement necessitates the utilization of all five classes. Furthermore, in mobile applications that store seizure EEG signals during episodes for subsequent diagnosis, capturing the location of the brain that exhibits abrupt signals becomes vital. Consequently, the classification of all five classes becomes necessary in such scenarios. However, it is important to acknowledge that classifying all five classes poses challenges, as EEG signals are complex in nature, and different states (or classes) are highly variable across patients.

3.3 $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et: Epilepsy Concatenation Network

Let us now delve into our model, called Epilepsy Concatenation Network ($\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et) illustrated in Figure 2 and explore its complexities. $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et is a hybrid model that combines parallel and sequential layers. It can accurately predict the onset of seizures to trigger alarms and can also find utilization in hospitals for diagnosing and localizing epilepsy. The core architecture of $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et consists of an input layer with a shape of (178, 1), followed by six parallel layer blocks called *DenseBlock* which gets concatenated into a single concatenation layer after feature extraction. These DenseBlocks take a parameter 'n' and features from the input layer, generating feature maps for the subsequent sequential model. The number of neurons is initially fixed upto 4 layers according to the number of neurons defined, then gets fixed to 128 neurons for the next two layers.

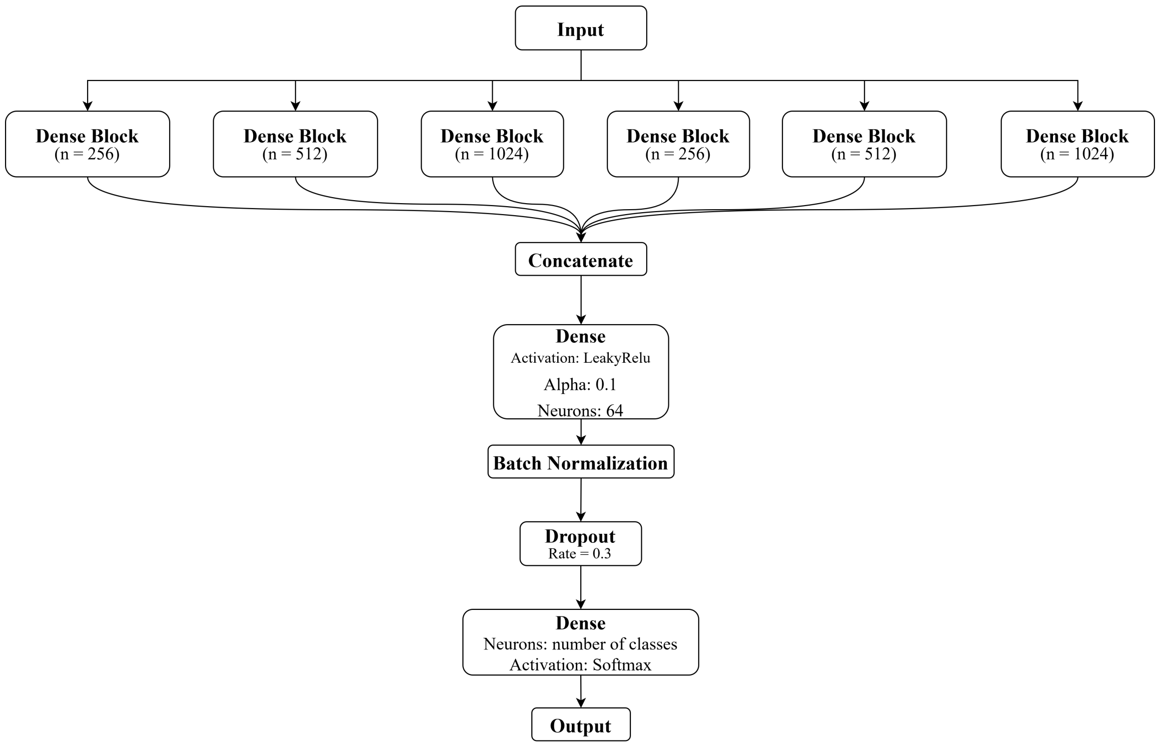

Figure 2: Core architecture of $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et. The parameter Alpha (α) is the default parameter in Leaky ReLU literature.

Subsequently, all the feature maps are combined seamlessly through concatenation, hence creating a unified and comprehensive learned representation embedding vector. These learned features are then passed through a dense layer with 64 neurons, which is linearly connected and utilizes a leaky ReLU activation function. To address the issue of internal covariance shift, the network's feature vectors undergo batch normalization. Additionally, a dropout layer is incorporated towards the end to mitigate potential overfitting problems. The final layer of the model is a softmax layer, providing classification probabilities for different classes.

Exploring the architecture of the **DenseBlock** shown in Figure 3. The **DenseBlock** first passes through Batch Normalization to speed up the training. Then it comprises a sequence of blocks composed of neurons ranging from 'n'(variable adjusted according to requirement) to 128 neurons as moved towards the end of the block. Each dense layer utilizes a leaky RELU activation function with an α value of 0.2 (a default parameter of leaky ReLU) and is followed by a dropout of 0.4 layer to prevent over-fitting. Next, we will compare the proposed architecture with existing state-of-the-art (SOTA) approaches on the ESRD dataset.

4 Experimental Analysis

In this section, we will now evaluate the effectiveness of our proposed approach by comparing it to various state-of-the-art (SOTA) methods on *benchmarking* real-world dataset. The complete experimental code

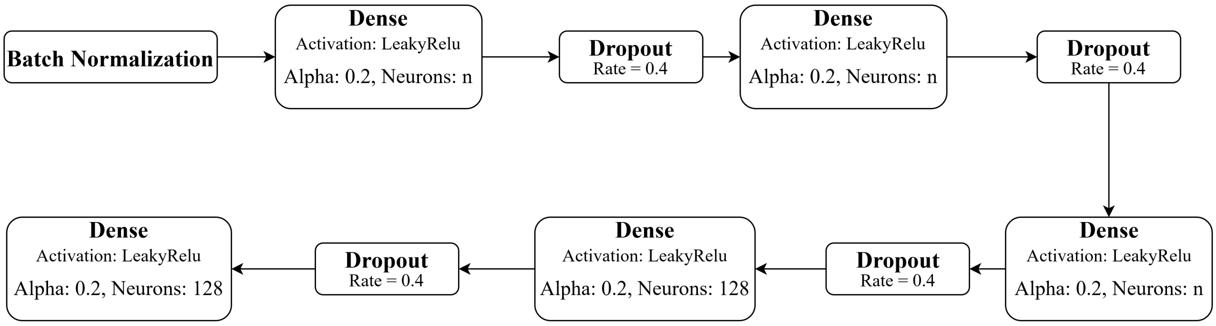

Figure 3: Architecture of Dense Block in $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et. The parameter Alpha (α) is the default parameter in Leaky ReLU literature.

is provided anonymously here[1]. The dataset utilized in this study has been thoroughly examined in Section 3.1. We opt for no feature extraction, feeding raw signals directly into the model to ensure architectural robustness at the hardware level for practical diagnostic purposes. Additionally, this design allows clinicians to effortlessly input raw data into the system, eliminating the need for pre-processing stages and longer waiting time before classification (or detection). Also, the results can be showcased without necessitating alterations to the model architecture and training algorithm even in scenarios involving multi-channel EEG data, thereby rendering it well-suited for real-time monitoring purposes.
Experimental Setup: All experiments are executed on Google Colaboratory Notebook, 24GB RAM with Python 3. $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et requires additional hyper-parameters, namely learning rate, epochs, and batch size. These are set to 0.0008, 500, and 700, respectively, across all classification problems using the $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model. The parameters for the baseline SOTA methods remained the same as reported in their original papers. The train test split is 80:20 and is consistent with previous literature [9, 10].

To address various applications, we categorize the problem of epileptic seizures into distinct tasks, which are as follows:
Task 1 (Binary Classification): In this task, our objective is to classify EEG signals from an individual as either belonging to a healthy individual or an individual with epilepsy. This task is particularly useful for initial diagnosis in hospitals. For classification purposes, we group class A and B together as one class and class C, D, or E as another class.
Task 2 (Ternary Classification): This task plays a crucial role in predicting the onset of seizures for IoT-based and alarming applications. To achieve this, we grouped classes A and B together as one class. class C and D form the second class, which signifies the triggering of a seizure. The third class, denoted by class E, represents the signals recorded during an epileptic seizure. This third class is particularly valuable for calling nearby emergency services in the event of prolonged seizures.
Task 3 (5-mode Classification): In this task, we treat each class in the original dataset as a separate class. The separation of class C and D aids in the further localization of the epileptic region in the brain.

The task division is consistent with prior literature [9, 10, 41, 44] and are compared on following metrics:

4.1 Performance Metrics

- **Accuracy** (Acc): This metric represents the ratio of correctly predicted instances to the total number of instances.

$$\text{Acc} = \frac{\text{Number of Correct Predictions} \times 100}{\text{Total Number of Instances}} \tag{1}$$

- **Loss**: This is a measure of the difference between predicted values and actual values, used during training to guide the optimization process. Generally, as the loss decreases, accuracy improves.

[1]https://github.com/sg-research08/EpilConNet.git

Specifically, we use the categorical cross-entropy loss function ($\mathcal{L}(\cdot)$), defined for N classes as:

$$\mathcal{L}(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{2}$$

Here, y represents the true distribution (ground truth) of the categories, and $\hat{y}$ represents the predicted distribution of the categories, often obtained from a neural network or other classifier. These are typically represented as one-hot encoded vectors.

- **Precision**: This metric measures the accuracy of positive predictions made by a model. It is the ratio of true positive predictions to all instances predicted as positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

Where True Positives (TP) are instances correctly predicted as positive, and False Positives (FP) are instances incorrectly predicted as positive.

- **Recall**: Also known as sensitivity or the true positive rate, this metric measures the ability of a model to correctly identify all relevant instances out of the total actual positive instances.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

Where False Negatives (FN) are instances incorrectly predicted as negative when they are actually positive.

- **F1-Score**: This composite metric combines precision and recall into a single measurement to comprehensively assess a model's performance. It is particularly useful when class distributions are imbalanced or the costs of false positives and false negatives are significant. The F1-Score is calculated as follows:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

A good machine learning model has high accuracy (correspondingly lower loss), high precision, recall, and F1-score.

We begin by comparing the performance of our $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model with SOTA methods using the accuracy metric. The training and testing accuracies are presented in Tables 1 and 2, respectively. In the binary classification task, our $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model achieves similar performance to SOTA during training and outperforms all other methods during testing. In the case of ternary classification, where limited research has been conducted, our $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model achieves successful results. For the crucial five-mode classification task, our $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model surpasses the SOTA methods with a 4% increase in accuracy during training, while maintaining comparable accuracy during testing.

4.2 Analysis for Task 1: Binary Classification

In this section, we evaluate the performance of our $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model prevelant metric in literature, including precision, recall, and F1-score. The class-wise results can be found in Table 3, while the average results are presented in Table 4.

We also examine the training and testing trends of our $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model in binary classification to monitor the issue of over-fitting. The trends for both training and testing are depicted in Figure 4.

4.3 Analysis for Task 2: Ternary Classification

The precision, recall and F1-Score in ternary setting is available in Table 5 and Table 6. The learning curves for train and test phase are illustrated in Figure 5. The learning curves exhibit a smooth progression without any indications of over-fitting. The confusion report for the problem is also available in the same Figure.

Model/SOTA	Binary Classification	Ternary Classification	5-mode Classification
$\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et (Proposed)	99.95%	99.87%	98.61%
Hybrid CNN-LSTM [18]	94.98%	-	-
Hybrid 1D-CNN [11]	100%	99%	94%
Attention based CNN [40]	-	98.89%	-
EpilNet [10]	95.15%	-	82.58%
Woodbright et al [39]	98.65%	-	-
1D CNN-LSTM [41]	99.39%	-	82.00%
Gupta et al[9]	99.9%	-	-
CNN with feature fusion [6]	99.0%	-	-
LSTM [17]	99.0%	-	-
Chanu et al [5]	99.2%	-	-
Zhao et al[43]	97.63 - 99.52%	96.73 - 98.06%	93.55%
Turk and Ozerdem[32]	-	-	93.60%
Zahra et al**[42]**	-	-	87.2%
Bhattacharya et al**[3]**	99%	98.60%	-
Tzallas et al**[33]**	100%	-	89.00%
Wang et al**[38]**	-	95.4%	-
Shankar et al**[22]**	97.55%	-	-
Thara et al**[31]**	97.21%	-	-
Tzimourtla et al**[34]**	99.16%	95.84%	82.25%
Amin et al**[1]**	100.0%	-	-

Table 1: Training performance comparison of $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et against SOTA methods in different settings.

Model/SOTA	Binary Classification	Ternary Classification	5-mode Classification
$\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et (Proposed)	97.46%	91.65%	76.34%
Hybrid CNN-LSTM [18]	82.21%	-	-
EpilNet [10]	94.56%	-	79.13%

Table 2: Testing performance comparison of $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et against SOTA methods in different settings.

4.4 Analysis for Task 3: 5-mode Classification

Similar observations for 5-mode classification are summarized in Table 7, Table 8 and Figure 6. The consistent gap observed between the training and testing curves show that the model is converging effectively. The confusion matrix for 5-mode problem is also available in the same Figure.

Class	Precision	Recall	F1-Score
0	0.98	0.99	0.98
1	0.96	0.91	0.94

Table 3: Class-wise precision, recall and F1-Score on binary classification.

Performance Metric (Based on Average Score)	Precision	Recall	F1-Score
Macro Average	0.97	0.95	0.96
Weighted Average	0.97	0.97	0.97
Micro Average	0.97	0.97	0.97

Table 4: Average performance metric namely precision, recall and F1-Score for binary classification.

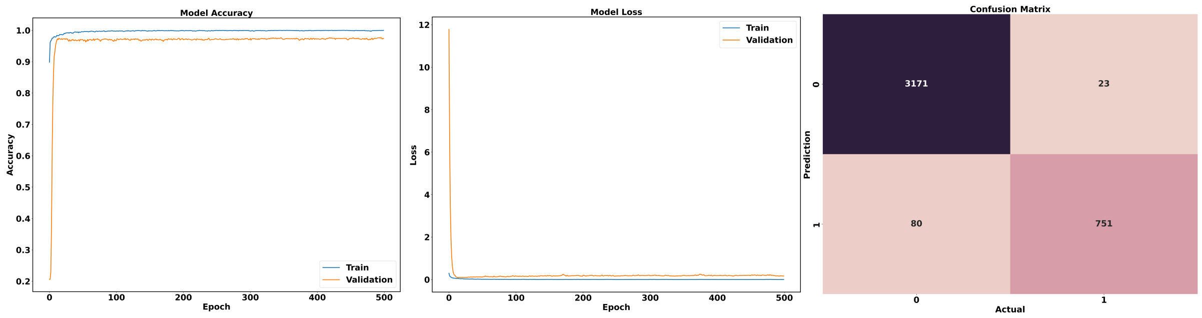

Figure 4: The figure shows plot for $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et (a) accuracy (b) loss. (c) Confusion matrix for binary classification.

Class	Precision	Recall	F1-Score
1	0.94	0.89	0.91
2	0.98	0.92	0.95
3	0.87	0.94	0.90

Table 5: Class-wise precision, recall and F1-Score on ternary classification.

Performance Metric (Based on Average Score)	Precision	Recall	F1-Score
Macro Average	0.94	0.89	0.91
Weighted Average	0.98	0.92	0.95
Micro Average	0.87	0.94	0.90

Table 6: Average performance metric namely precision, recall and F1-Score for ternary classification.

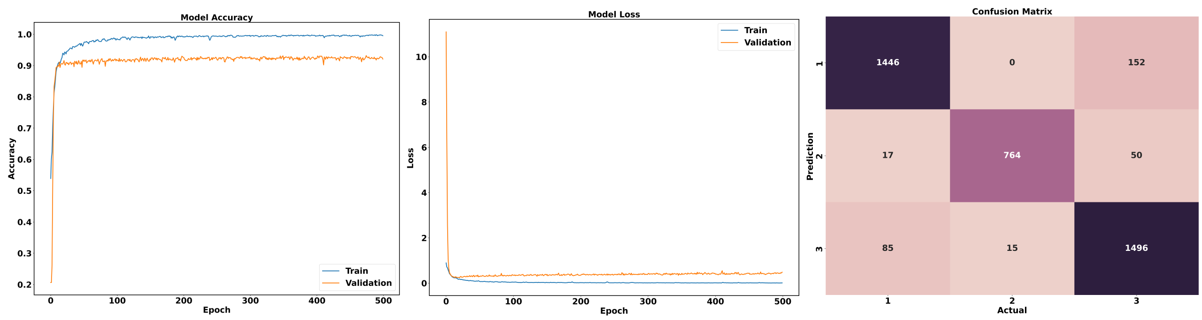

Figure 5: The figure shows plot for $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et (a) accuracy (b) loss. (c) Confusion matrix for ternary classification.

Class	Precision	Recall	F1-Score
1	0.99	0.91	0.95
2	0.72	0.65	0.68
3	0.65	0.76	0.70
4	0.80	0.72	0.75
5	0.70	0.78	0.74

Table 7: Class-wise precision, recall and F1-Score for 5-mode classification.

Performance Metric (Based on Average Score)	Precision	Recall	F1-Score
Macro Average	0.77	0.76	0.76
Weighted Average	0.77	0.76	0.77
Micro Average	0.76	0.76	0.76

Table 8: Average performance metric for 5-mode classification.

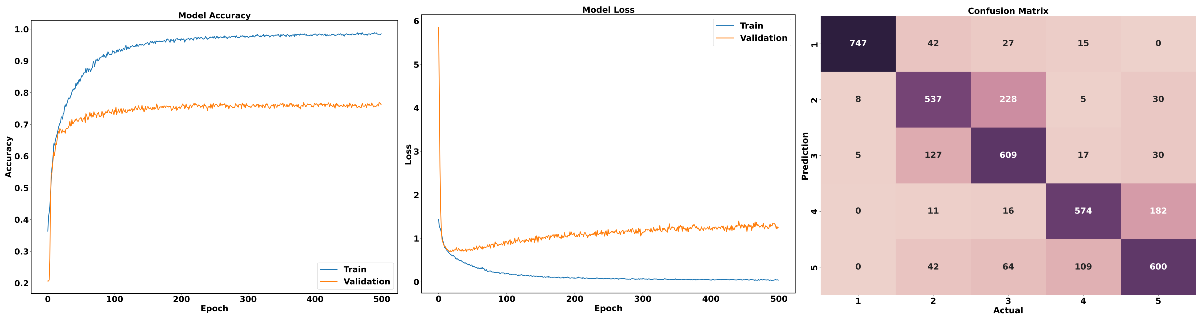

Figure 6: The figure shows plot for $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et (a) accuracy (b) loss. (c) Confusion matrix for 5-mode classification.

4.5 Ablation Study

In this subsection we conduct an ablation study to demonstrate the proposed model's generalization capability on smaller training data scenarios that are quite evident in medical diagnosis. We report the training and testing accuracy over ten independent runs. Each run is executed with a different value to ensure that the study captures the diversity of the sub-sampled dataset. The study is conducted for all three different settings: binary classification, ternary, and 5-mode classification, and results are reported in Figure 7 (a), (b) and (c) respectively. It can be observed from the reported performance graphs that in binary classification, even with just scarce availability of around 20 to 40% of complete data, the proposed model is able to achieve training accuracy of orders comparable to state-of-the-art (SOTA) methods. Moreover, the testing accuracy has quite stable performance even at 50% availability of data and remains considerably well around 90% even with just 20% sub-sampled dataset. Next, as the problem complexity slightly increases in ternary classification, the training performance remains considerably high. There is a slight drop in testing accuracy, but it remains above 83% and goes as high as the mean value of 91.6%. In the most challenging scenario of 5-way (or mode) classification, even with only 20 to 30% of the dataset available, the training accuracy remains comparable to the state-of-the-art (SOTA) performance shown in Table 1, which is based on training with 100% of the dataset.

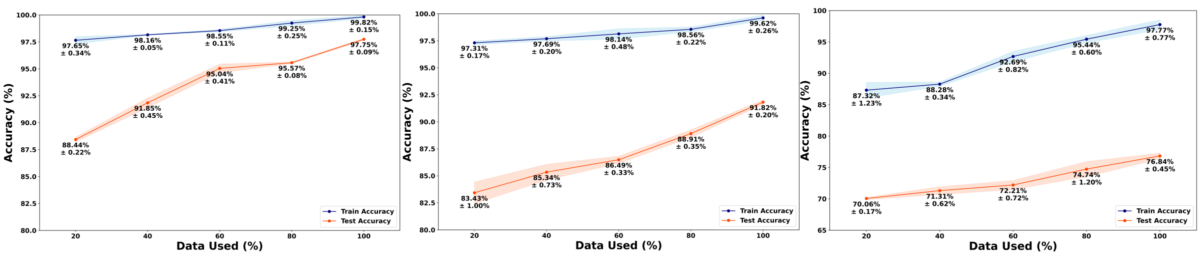

Figure 7: The figure shows the plot for $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et's accuracy for (a) binary, (b) ternary, and (c) 5-mode classification on varying dataset sizes.

5 Discussion

In this section, a detailed discussion is carried out for both results in Table 1 and 2.

5.1 Comparison against binary classification

Table 1 outlines the initial work in epilepsy seizure detection for signal classification into seizure and non-seizure classes by [33]. Their utilization of time-frequency analysis resulted in a 100% accuracy in training, with a lack of reported testing performance, suggesting potential overfitting. Subsequent advancements in technology and machine learning algorithms led [3] to extract features through wavelet transformation, achieving a 99% accuracy with support vector machines (SVM). In a close approach, [34] employed wavelet transform in all three settings, achieving reasonable accuracy. Another study by [31] adopted a similar idea by utilizing seven feature extraction methods fed into a three-layer deep neural network, demonstrating comparable performance. The rise of ensemble learning, exemplified by [41, 11, 18] and [1], showcased stacked ensembles of $1d$ convolutional networks with long short-term memory (LSTM) networks and weighted ensembles of various ML methods (SVM, Naive Bayes, k-Nearest Neighbor, and Multi-Layer Perceptron). All these ensembles achieved accuracy close to optimal classification as the binary problem is less challenging than other settings, as visualized in Figure 1. The surge in interest for unsupervised algorithms motivated [22] to employ PCA followed by neural networks, with a slight performance decrease of 2-3%. Later, [5] incorporated self-organizing neural networks and Multi-Layer Perceptron with genetic algorithms, enhancing accuracy in unsupervised learning. In our proposed $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et, leveraging a parallel architecture played a crucial role in achieving comparable train and test accuracy, surpassing the SOTA performance. Additionally, [39] incorporated explainability into binary classification models through decision trees, achieving 98% accuracy. However, there remains scope for improvement and achieving SOTA binary classification models while simultaneously providing user explanations.

5.2 Comparison against ternary classification

In this context, similar observations emerge, with initial works employing wave analysis for EEG data classification, achieving an accuracy of 95.84% ([34]) and 98.60% ([3]). A slightly different approach was adopted by [38], utilizing gradient boosting methods with symlet wave processing for feature extraction. On similar lines to binary classification, integrating $1d$ convolution contributed to higher accuracy. Nevertheless, our proposed $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et architecture surpasses the SOTA performance on both training and test data, highlighting the efficacy of our approach across the complete dataset and facilitating the achievement of a better-generalized model.

5.3 Comparison against 5-mode classification

Expanding the classification framework to encompass all five classes, [42] incorporated instantaneous amplitude and EEG data frequency. This approach marked a starting achievement, yielding an accuracy of 87.2% in the 5-class setting. Seeking performance enhancement, [32] employed Morlet Continuous Wave to transform EEG signal data into scalogram images, which, when fed into a two-convolution-layer network, resulted in a substantial performance boost to 93.6%. Building upon this progress, [43, 9, 10] harnessed the power of $1d$ convolutional networks, pushing the accuracy further to 94%. However, integrating a combined parallel and sequential model proposed $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et proved pivotal in extracting superior features. This, coupled with the utilization of leaky ReLU, contributed to a notable increase of approximately 3% in train and test accuracy, showcasing improved epilepsy diagnosis capabilities.

6 Conclusion and Future Directions

This paper proposes a novel $\mathcal{E}$pil$\mathcal{C}$on$\mathcal{N}$et model that outperforms current SOTA approaches on all binary, ternary, and 5-mode classifications. The model can be used for quick diagnosis at first help (healthy vs epileptic case), in mobile applications for the onset of seizure prediction (ternary), and for localization and diagnosis at hospitals (5-mode problem). The model is easy to tune for hyper-parameters, such as the learning rate across all the classification problems. An interesting future direction is integrating this model into real-world systems, providing a comprehensive solution for epilepsy diseases. Apart from those mentioned above, other immediate future directions can be combining the model with wavelet analysis for feature extraction and analyzing performance under reduced. EEG capture length ([24]).

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Code availability: The code has been made publicly available at `https://github.com/sg-research08/EpilConNet.git`

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