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Classification of Epilepsy Diagnostic Results through EEG Signals Using the Convolutional Neural Network Method

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ABSTRACT

The brain is one of the most important organs in the human body as a central nervous system which functions as a controlling center, intelligence, creativity, emotions, memories, and body movements. Epileptic seizure is one of the disorder of the brain central nervous system which has many symptoms, such as loss of awareness, unusual behavior and confusion. These symptoms lead in many cases to injuries due to falls, biting one's tongue. Detecting a possible seizure beforehand is not an easy task. Most of the seizures occur unexpectedly, and finding ways to detect a possible seizure before it happens has been a challenging task for many researchers. Analyzing EEG signals can help us obtain information that can be used to diagnose normal brain activity or epilepsy. CNN has been demonstrated high performance on detection and classification epileptic seizure. This research uses CNN to classify the epilepsy EEG signal dataset. AlexNet and LeNet-5 are applied in CNN architecture. The result of this research is that the AlexNet architecture provides better precision, recall, and f1-score values on the epilepsy signal EEG data than the LeNet-5 architecture.

Keywords: EEG Signal; Epileptic Seizure; CNN; AlexNet; LeNet-5

1. INTRODUCTION

The brain is one of the most important organs in the human body as a central nervous system (CNS) which functions as a controlling centre, for intelligence, creativity, emotions, memories, and body movements. Inside the brain, there are neuron cells that are connected through synapses to deliver information when responding to a stimulus. The process of sending this information through electricity transmission as a result of neuronal cell biopotential activity. Under normal conditions or healthy people, this electrical activity is found in all area of the brain and then produces brain waves that can be studied. When the electrical cells of neurons disrupted by either excessive activity or loss of the function of biopotential signal transmission, it can cause brain function disorders. One of the effects of abnormalities in electrical functions is epilepsy, which is generally characterized by body seizures and merely stares blankly for a few seconds during a seizure with a specific duration. According to WHO, Epilepsy is one of the most common neurological disorders. Based on a survey, about 50 million people worldwide have epilepsy [1].

Epileptic seizures have many symptoms, such as loss of awareness, unusual behavior and confusion. These symptoms lead in many cases to injuries due to falls, biting one's tongue. Detecting a possible seizure beforehand is not an easy task. Most of the seizures occur unexpectedly, and finding ways to detect a possible seizure before it happens has been a challenging task for many researchers [2].

Mostly, such patients are monitored and examined using electroencephalogram (EEG) recordings. These recording are then visually analyzed by doctors for a more comprehensive understanding of the patient's seizures. Due to the rapid development of computer technology, seizure detection and classification of seizure types on EEG signals can be done by applying digital signal processing using simple and even complex methods. Analyzing the EEG signal can help get information that can be used to diagnose normal brain activity or epilepsy [3]. The component of EEG signal frequency informs the state of the brain and the visual observation of EEG signal is very difficult considering that the amplitude of EEG signal is very low and the pattern is very complex [4].

A number of research on the classification of EEG signals has been carried out by several researchers. Previous studies used several different classification methods, such as random forest classifier, k-nearest neighbor (K-NN), naïve bayes, logistic regression, decision tree (D.T.), random tree, J48, stochastic gradient descent (S.G.D.). The result was that the random forest classifier outperforms other classification methods with an accuracy of 97.08%, ROC 0.996, and RMSE 0.1527 [2]. The combination method using singular spectrum analysis (SSA) for noise removal, power spectral density (PSD) as feature extraction and CNN as a classifier could increase the average classification accuracy results [5]. Another combination method using continuous wavelet transform (CWT) and convolutional neural network (CNN) was proposed to classify epileptic seizures and obtain an accuracy of 72.49% and a loss of 0.596 [6]. CNN based on multi-segment EEG signal to classify epilepsy EEG signal showed better performance than without segment [7]. Another research was designing CNN based deep learning structures to detect epilepsy using EEG signals. CNN training was carried out using a cross-validation technique. From the simulation results, it was obtained that the average accuracy level for the test achieved was 98.67%, 97.67% sensitivity and 98.83% specificity [8]. Based on these studies, CNN is able to classify EEG signals properly and precisely.

Nowadays, most image processing and computer vision-related problems apply CNN for a better solution. The reason behind the better performance of CNN in the above said task is its ability to work on raw data without having prior knowledge [9]. CNN have shown remarkable superiority in various real-world applications over most machine-learning approaches [10]. the CNN method was chosen as a method for the classification of epileptic EEG signals because it has a deep learning algorithm that can select features optimally based on the loss function to achieve high performance in classifying images [7]. CNN has been demonstrated high performance on image classification and pattern detection [6]. The accuracy of classification using CNN based on multi segment EEG signal was 99.33-100% [7]. The classification results of epilepsy EEG signals using the CNN technique and cross-validation obtained an average accuracy rate of 98.67%, a sensitivity of 97.67%, and a specificity of 98.83% [11]. AlexNet and LeNet-5 architectures are CNN architectures which have a higher average success rate than the other architectures [12]. CNN for pattern recognition using the Lenet-5 architecture can achieve an accuracy of more than 98% [13]. CNN for image classification using AlexNet architecture showed average accuracy of 85% [14].

Thus, this study aims to help neurologists determine whether a person is having an epileptic seizure by observing the EEG signal recording using the CNN method.

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Based on the differences in accuracy results in different cases on the AlexNet and LeNet-5 architectures, this study will examine the classification of epilepsy diagnosis results by recording EEG signals using the CNN method, the architectures used are AlexNet and LeNet-5.

2. MATERIAL AND METHODS

This study uses the Convolutional Neural Network (CNN) method to classify epilepsy EEG signal datasets. There are two architectures used, namely AlexNet and LeNet-5. Algorithm performance will be evaluated using a confusion matrix.

2.1 RESEARCH STAGES

The stages of this research can be seen in Figure 1. The first stage, the epilepsy EEG signal dataset in Figure 2 will be preprocessed using the MinMax normalization method so that a better consistency and data quality value can be seen in Figure 3.

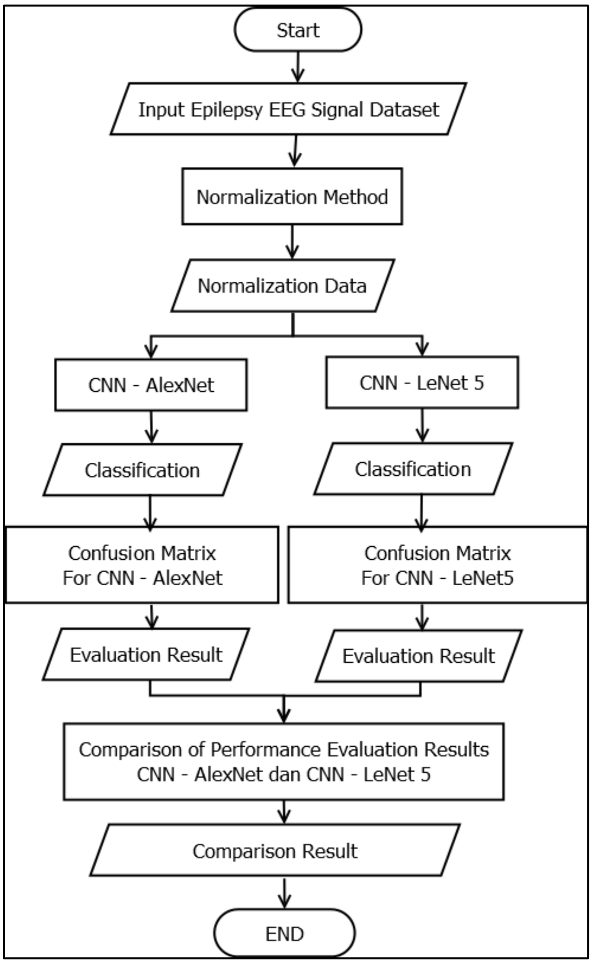

FIGURE 1. Research Stages

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	...	X170
0	135	190	229	223	192	125	55	-9	-33	-38	...	-17
1	386	382	356	331	320	315	307	272	244	232	...	164
2	-32	-39	-47	-37	-32	-36	-57	-73	-85	-94	...	57
3	-105	-101	-96	-92	-89	-95	-102	-100	-87	-79	...	-82
4	-9	-65	-98	-102	-78	-48	-16	0	-21	-59	...	4
...	...	...	...	...	...	...	...	...	...	...	...	...
11495	-22	-22	-23	-26	-36	-42	-45	-42	-45	-49	...	15
11496	-47	-11	28	77	141	211	246	240	193	136	...	-65
11497	14	6	-13	-16	10	26	27	-9	4	14	...	-65
11498	-40	-25	-9	-12	-2	12	7	19	22	29	...	121
11499	29	41	57	72	74	62	54	43	31	23	...	-59

FIGURE 2. Epilepsy EEG Signal Dataset

	0	1	2	3	4	5	6	7
0	0.104109	0.146523	0.176599	0.171972	0.148066	0.096397	0.042415	-0.006941
1	0.061209	0.060575	0.056452	0.052488	0.050743	0.049951	0.048682	0.043132
2	-0.038444	-0.046854	-0.056465	-0.044451	-0.038444	-0.043250	-0.068479	-0.087701
3	-0.111276	-0.107037	-0.101738	-0.097499	-0.094319	-0.100678	-0.108096	-0.105977
4	-0.017182	-0.124093	-0.187094	-0.194730	-0.148911	-0.091638	-0.030546	0.000000
...	...	...	...	...	...	...	...	...
11495	-0.042703	-0.042703	-0.044644	-0.050468	-0.069878	-0.081525	-0.087348	-0.081525
11496	-0.021589	-0.005053	0.012861	0.035369	0.064766	0.096920	0.112997	0.110241
11497	0.023487	0.010066	-0.021809	-0.026842	0.016776	0.043618	0.045296	-0.015099
11498	-0.040310	-0.025194	-0.009070	-0.012093	-0.002015	0.012093	0.007054	0.019147
11499	0.043894	0.062058	0.086275	0.108979	0.112006	0.093843	0.081734	0.065085

FIGURE 3. Normalization Epilepsy EEG Signal Dataset

This study conducted 6 experimental scenarios as shown in Table 1, where the dataset is divided into two parts, namely the training dataset and the testing dataset. Furthermore, the dataset is processed using the CNN – AlexNet and CNN – LeNet 5 methods. The results of the classification of the two methods are evaluated using the confusion matrix to obtain precision, recall, f1-score values and accuracy. The confusion matrix values of the 6 trial scenarios will be compared to determine the best value.

TABLE 1.
Experiment Table

Scenario	Training Data (%)	Testing Data (%)	Architecture
1	90	10	*AlexNet*
2	80	20	*AlexNet*
3	70	30	*AlexNet*
4	90	10	*LeNet-5*
5	80	20	*LeNet-5*
6	70	30	*LeNet-5*

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2.2 MATERIAL

In designing the classification of epilepsy EEG signals using the CNN method, the epilepsy dataset used was downloaded from Kaggle. The dataset consists of 11500 information data, each information data has 178 features which indicate the measurement of brain waves per second. The data is grouped into five different classes Y = {1,2,3,4,5} [6] with the following criteria :

a) 5 - eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open
b) 4 - eyes closed, means when they were recording the EEG signal the patient had their eyes closed
c) 3 - Yes they identify where the region of the tumor was in the brain and recording the EEG activity from the healthy brain area
d) 2 - They recorder the EEG from the area where the tumor was located
e) 1 - Recording of seizure activity

2.3 CONVOLUTIONAL NEURAL NETWORK (CNN)

The classification method in this study is the CNN method. CNN has been used frequently in recent years and is the most popular method in deep neural networks. CNN has four main layers: the convolutional layer, non-linear layer, pooling layer, and fully connected layer.

Convolutional layers are a process whereby images are manipulated using external masks or subwindows to produce new images. This process is reducing the dimensions of the image with convolutional operations to extract important features from the image such as feature/edge detection, color, gradient orientation, etc. through an encoding process [15].

The non-linear layer is used to adjust or trim the resulting output. This layer is applied to limit the resulting output. Currently, the Rectified Linear Unit (ReLU) method is more often used because it has a simpler definition both in terms of function and gradient.

In this part of the pooling layer, the process of reducing the size of an image data occurs. In image processing, pooling also aims to increase the position invariance of features and speed up computation and control overfitting. This layer is also responsible for reducing dimensions [15].

The fully connected layer is similar to the way neurons are arranged in a traditional artificial neural network. Therefore, every node in the fully connected layer is directly connected to every node in either the previous layer or the next layer [16].

2.3.1 CNN ARCHITECTURE

2.3.1.1 ALEXNET

The AlexNet architecture consists of 5 convolution layers, 3 pooling layers, 2 dropout layers, and 3 fully connected layers [17].

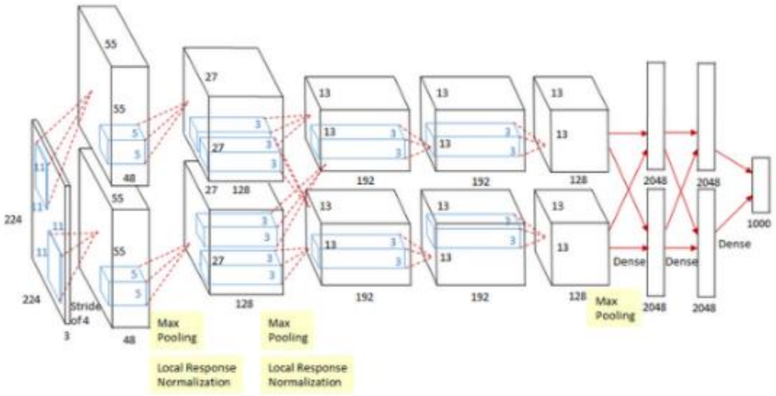

FIGURE 4. AlexNet Architecture [17]

2.3.1.2 LENET-5

LeNet-5 is a CNN-based multi-layer network first introduced by Yann LeCun. Along with the development and advancement of computer technology, the LeNet-5 layer has increased so that computers can perform computations or mathematical calculations more quickly [18].

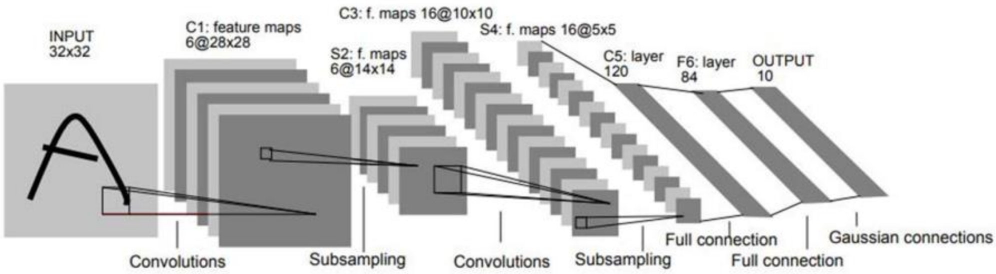

FIGURE 5. LeNet-5 Architecture [18]

2.4 CONFUSION MATRIX

Confusion matrix is one of the methods used to evaluate the performance of the classification algorithm [15]. The confusion matrix is presented in the form of a table which states the classification of the number of correct test data and the number of incorrect test data as shown in Figure 9 and has several parameters for evaluating the performance of the resulting classification model [19] :

$$Precission = \frac{TP}{(TP + FP)} \quad (1)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (2)$$

$$F1 - Score = \frac{(2 \times Recall \times Precission)}{(Recall + Precission)} \quad (3)$$

$$Accuracy = \frac{(TP + TN)}{Total} \quad (4)$$

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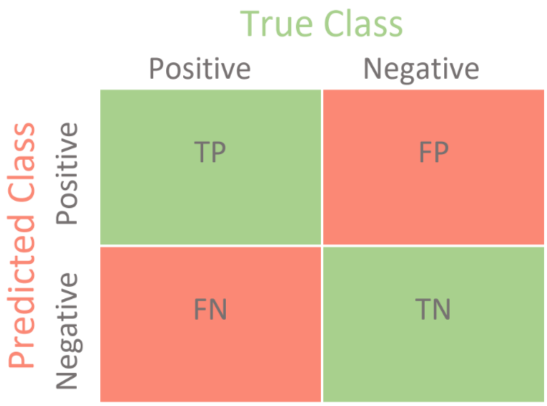


FIGURE 6. Confusion Matrix

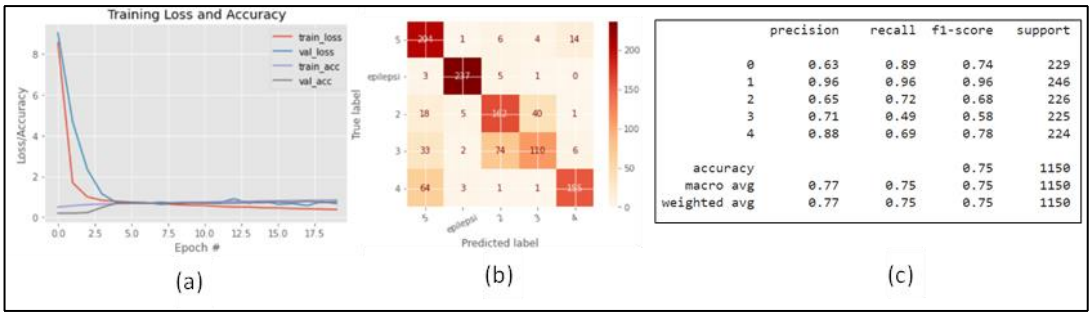
Description:

a) TP (True Positive) : Observation is predicted positive and is actually positive
b) TN (True Negative) : Observation is predicted negative and is actually negative
c) FP (False Positive) : Observation is predicted positive and is actually negative
d) FN (False Negative) : Observation is predicted negative and is actually positive

3. RESULT AND DISCUSSION

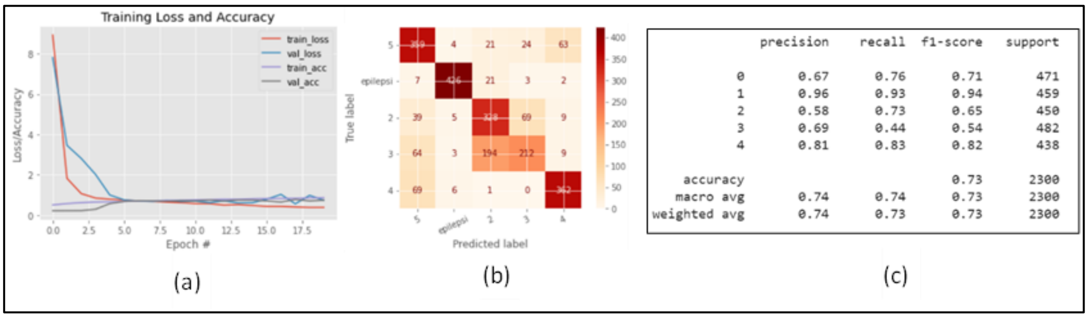
The results obtained from the classification of epilepsy EEG signals using the CNN method by applying two architectures, namely AlexNet and LeNet-5 will be presented in this section. This study conducted 6 experimental scenarios as shown in Table 1. Each experiment was examined for precision, recall, f1-score and accuracy. Then these values are compared to determine the best value. The experimental results of all scenarios can be seen in Figure 10 to Figure 15.

Based on experiment 1 as shown in Figure 10, it was found that CNN was able to classify EEG signals correctly in 237 out of 246 data with an accuracy rate of 75%, a precision value of 96%, a recall of 96%, and an f1-score of 96%. In experiment 2 as shown in Figure 11, the EEG signal data results were correctly classified as many as 426 out of 459 data with an accuracy rate of 73%, 96% precision, 93% recall, and 94% f1-score. Subsequent experiments, as shown in Figure 12, showed that CNN was able to accurately classify EEG signals as many as 588 out of 675 data with an accuracy rate of 73%, a precision value of 99%, a recall of 87%, and an f1-score of 93%.



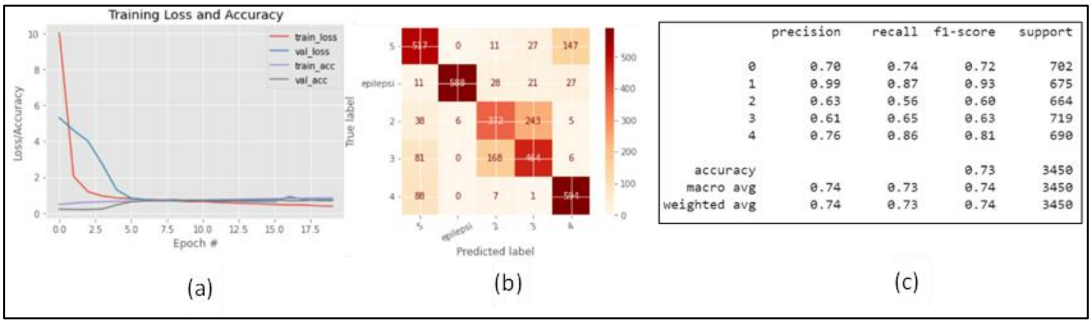
	precision	recall	f1-score	support
0	0.63	0.89	0.74	229
1	0.96	0.96	0.96	246
2	0.65	0.72	0.68	226
3	0.71	0.49	0.58	225
4	0.88	0.69	0.78	224
accuracy			0.75	1150
macro avg	0.77	0.75	0.75	1150
weighted avg	0.77	0.75	0.75	1150

FIGURE 7. Classification Results in Experiment 1



	precision	recall	f1-score	support
0	0.67	0.76	0.71	471
1	0.96	0.93	0.94	459
2	0.58	0.73	0.65	450
3	0.69	0.44	0.54	482
4	0.81	0.83	0.82	438
accuracy			0.73	2300
macro avg	0.74	0.74	0.73	2300
weighted avg	0.74	0.73	0.73	2300

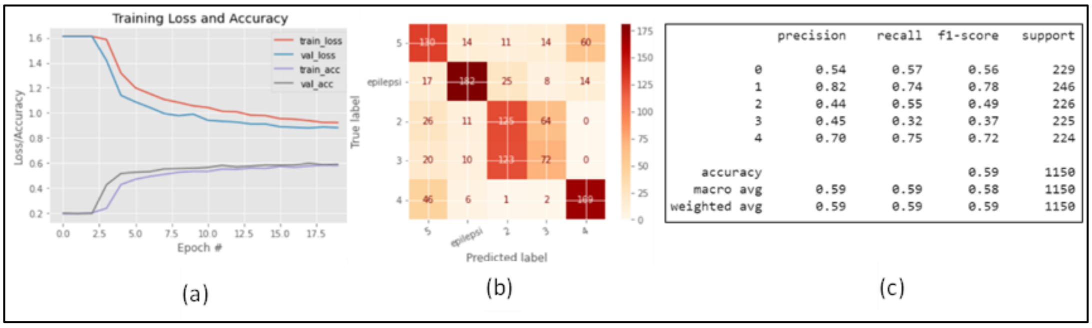
FIGURE 8. Classification Results in Experiment 2



	precision	recall	f1-score	support
0	0.70	0.74	0.72	702
1	0.99	0.87	0.93	675
2	0.63	0.56	0.60	664
3	0.61	0.65	0.63	719
4	0.76	0.86	0.81	690
accuracy			0.73	3450
macro avg	0.74	0.73	0.74	3450
weighted avg	0.74	0.73	0.74	3450

FIGURE 9. Classification Results in Experiment 3

Based on experiment 4 as shown in Figure 13, it was found that CNN was able to correctly classify 182 of the 246 EEG signals with an accuracy rate of 59%, a precision value of 82%, a recall of 74%, and an f1-score of 78%. In experiment 5 as shown in Figure 14, the results of EEG signal data were correctly classified as many as 222 out of 459 data with an accuracy rate of 444%, a precision value of 58%, a recall of 48%, and an f1-score of 53%. The last experiment, as shown in Figure 15, showed that CNN was able to accurately classify EEG signals in 417 out of 675 data with an accuracy rate of 58%, a precision value of 85%, a recall of 62%, and an f1-score of 72%.



	precision	recall	f1-score	support
0	0.54	0.57	0.56	229
1	0.82	0.74	0.78	246
2	0.44	0.55	0.49	226
3	0.45	0.32	0.37	225
4	0.70	0.75	0.72	224
accuracy			0.59	1150
macro avg	0.59	0.59	0.58	1150
weighted avg	0.59	0.59	0.59	1150

FIGURE 10. Classification Results in Experiment 4

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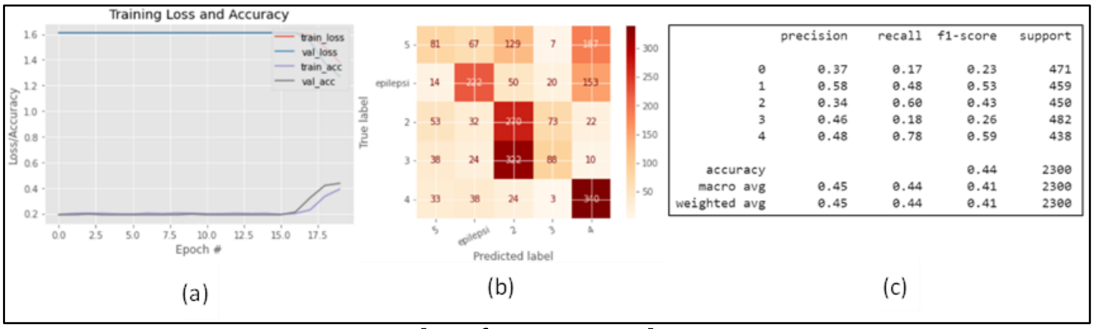

FIGURE 11. Classification Results in Experiment 5

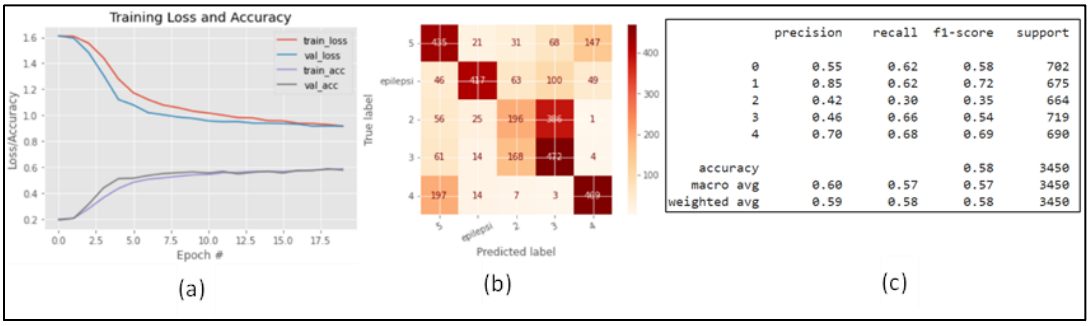

FIGURE 12. Classification Results in Experiment 6

The following table shows the overall test results by scenario.

TABLE 2.
Confusion Matrix For Each Experiment

Scenario	Training Data (%)	Testing Data (%)	Architecture	Confusion Matrix			Accuracy
				Precission	Recall	F1-Score	
1	90	10	*AlexNet*	96%	96%	96%	75%
2	80	20	*AlexNet*	96%	93%	94%	73%
3	70	30	*AlexNet*	99%	87%	93%	73%
4	90	10	*LeNet-5*	82%	74%	78%	59%
5	80	20	*LeNet-5*	58%	48%	53%	44%
6	70	30	*LeNet-5*	85%	62%	72%	58%

Based on the results of the six experiments that have been carried out, the amount of training data affects the values of accuracy, precision, recall, and f1-score. In addition, the layers and the number of architectural parameters also affect the level of classification accuracy. The AlexNet architecture has 21.114.629 parameters, 5 convolution layers, 3 pooling layers, 2 dropout layers, and 3 fully connected layers, while the LeNet-5 parameters total 93,597 parameters, 2 convolution layers, 2 pooling layers, 2 dropout layers, and 3 fully connected layers. So that in epilepsy EEG signal research, the AlexNet architecture provides a higher accuracy value.

4. CONCLUSION

Based on the classification results of epilepsy EEG signals using the CNN method with the AlexNet and LeNet-5 architectures, the use of the AlexNet architecture provides higher accuracy, precision, recall, and f1-score results for epilepsy EEG signal data than the use of the LeNet-5 architecture. In future research, it is expected to be able to use datasets from different sources that use other architectures, such as GoogleNet, ResNet, VGG, Inception V4, change the type of activation function, change the type of pooling layer function, change the learning rate and number of epochs to get higher results.

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