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Early Study in Automatic Identification of Epilepsy in Neonatal Using EEGLAB and One Dimensional Convolutional Neural Network Through the EEG Signal

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Abstract

In detecting epileptic activity, medical experts examine the visual result of Electroencephalography signals. The visual analysis will take a lot of time and effort, due to a large amount of data. Furthermore, there are some errors in concluding the analysis result. One of the ways to analyze this quickly is to use Machine Learning (ML) methods. This study aims to evaluate the performance of 1D-CNN in identifying the given data. First, the signal will go through pre-processing using EEGLAB Toolbox which is then classified to identify epilepsy and non-epilepsy with the 1D-CNN algorithm. The results showed that the proposed method obtained high accuracy values, respectively 99,078% for the training data and 82,069% for the validation results. From the evaluation by a confusion matrix, an average accuracy of 99,31% was obtained. Based on this evaluation, the proposed model can be used as an efficient method in the process of automatic classification, detection, or identification of epileptic activity.

Keywords: *Confusion Matrix; EEG; EEGLAB; Epilepsy.*

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INTRODUCTION

Epilepsy is a chronic disorder of the brain due to the excessive production of electrical impulses and is often followed by loss of consciousness [1, 2]. The Covid-19 pandemic that occurred in the world in early 2020 has had a huge impact on all aspects. One of them is on health, i.e., epilepsy. Several epilepsy organizations have expressed their findings regarding the effect of Covid-19 on epilepsy. The Epilepsy Foundation informed that 1 in 4 people with epilepsy experienced more seizure frequency during the Covid-19 pandemic [3]. The International League Against Epilepsy (ILAE) also stated that there is a risk that people with epilepsy will get worse if infected with Covid-19 [4]. This is due to Covid-19 making sufferers

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experience fever or stress, which will increase the risk and frequency of seizures. Moreover, epilepsy is one of the most common neurological diseases globally, with as many as 50 million people worldwide having epilepsy [5], calculated from all age ranges, ethnicities, ages, and genders.

In this study, we discuss epilepsy that has occurred in neonates. Neonatal epilepsy can be a common indicator of dangerous neurological diseases such as hypoxic-ischemic encephalopathy and even stroke. Neonatal epilepsy is usually a subclinical event [6], in which, from a neurological point of view, the underlying cause of epilepsy remains unclear [7]. This type of epilepsy is sometimes inferred to be a common brain disease, such as brain injury or even a tumor [8]. Therefore, according to medical experts, epilepsy can only be detected using EEG. So, to detect this requires a medical person who is highly trained and skilled in the field. However, in general, manually reading visual EEG results will take a lot of time and most of the results are inaccurate, which allows fatal errors in diagnosing results in the epilepsy treatment process [9]. With the advancement of technology, to overcome these problems, a handful of researchers in computational science try to help through automatic and intelligent programming specifically designed to assist neurologists in detecting epilepsy produced through EEG recording results or known as seizure detection algorithm (SDA) [10]. In this case, machine learning is used to automatically detect epilepsy in neonates.

Usually, the algorithms used for the classification process are K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Support Vector Machine (SVM). These three have been applied to many cases such as epilepsy detection using KNN [11] to classify epilepsy and non-epilepsy with 87% accuracy. In addition, using ANN [12] with 97.55% accuracy and using the EEG-focal and non-focal classification approach using SVM [13] with an accuracy of about 96.8%. The three algorithms have been used for a long time, and they have a disadvantage in that they cannot be used in large-scale data [14]. Therefore in 2006, Hinton, Osindero, and Teh suggested a new algorithm that can be used for larger networks known as DL (Deep Learning) [15]. CNN is one of the DL models that has been established as a standard machine learning operation recently and excels the most in the computer vision field of study [16].

Therefore, CNNs have also been used to perform classification in epilepsy and non-epilepsy. For example, in the study [6], the author compares SVM and CNN. It is found that the accuracy of the resulting CNN is higher than SVM, which is around 97.1% for CNN dan 82,9% for SVM. Another study [8] identifies epilepsy by comparing SVM, ANN, and CNN. The author found great results in CNN of 95.99%. A study using LRCN [17] to classify epileptic and non-epileptic data shows 93.4% accuracy. Even a study [18] tried to classify epilepsy through an EEG spectrogram and classified using CNN resulted in 77.57% accuracy. A study [19] performs the automatic detection of epilepsy with a hybrid 1D(One Dimensional)-CNN method from EEG signals and shows an accuracy of 94%-98%. From several previous studies that used CNN, the results were very high and quite accurate. Nevertheless, certain studies employ intricate algorithms that yield suboptimal accuracy values. Therefore, this study will propose a simple classification model using a CNN algorithm model to identify epilepsy and non-epilepsy in neonatal by using another method in pre-processing with the EEGLAB toolbox from MATLAB and identifying epilepsy using the 1D-CNN algorithm model.

The algorithm can be used to automatically identify epilepsy in clinical practice that does not spend a lot of time and effort. In addition, it is hoped that this research can be useful to help and facilitate a neurologist in identifying epilepsy efficiently and the accurate results obtained

can be used as validation for doctors when diagnosing, to reduce errors in deciding the results of identification or diagnosis.

METHOD

In this study, we propose an automatic method to classify epileptic diseases. The process can be explained simply in Figure 1. Our method is divided into two main steps including pre-processing and classification.

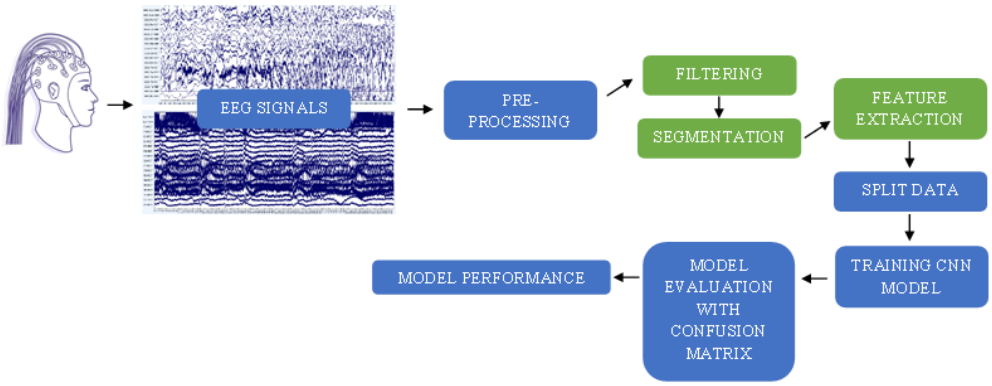


Figure 1. Schematic Overview of Neonatal Seizure Detection Using the 1D-CNN Algorithm

The first step is pre-processing which consists of filtering, segmentation, and feature extraction. This pre-processing is done using the EEGLAB Toolbox on MATLAB software [20]. The filtering process is performed using a Butterworth Band Pass Filter with a cut-off frequency of 0.5 Hz - 70 Hz [21] to remove noise or artefacts generated by the data during the recording process. Then, the data will be segmented to see more clearly which signals are experiencing epilepsy and which are not. And finally, the data will go through the feature extraction stage, which is done to find the characteristics of the data, before entering the classification stage, Feature extraction is performed using the Fast Fourier Transform (FFT), which has a mathematical equation [22] of

$$x(f) = \int_{-\infty}^{\infty} x(t)\, sin2\pi ft\, dt \quad (1)$$

and produces frequency spectrum features through Power Spectra Density (PSD). The data will then be normalized using z-score normalization [23]:

$$X' = \frac{X-\mu}{\sigma} \quad (2)$$

The second stage is the classification process. This stage is used to detect and classify epilepsy with the 1D-CNN algorithm. This stage uses Google Colaboratory which is used as a data storage area that will be used for the model evaluation process. After the classification process using the 1D-CNN model and generating training accuracy values, the data will be evaluated using the confusion matrix method.

Dataset

The dataset used in this study comes from neonate (infant) patient records provided by the Neonatal Intensive Care Unit (NICU), at Helsinki University Hospital. It is a public dataset that is open source and can be accessed through the Zenodo website [24]. This dataset is derived from 79 infant patients (neonates) diagnosed with epilepsy (seizures) and not accompanied by epilepsy (non-convulsions). However, only 38 patient records were used in this study, for the

reason of saving data processing time, as the more data used, the longer the data processing will take.

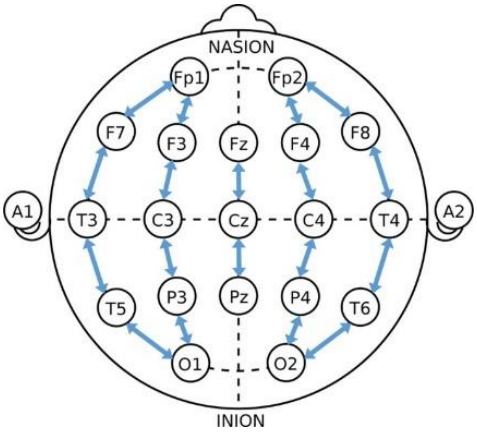
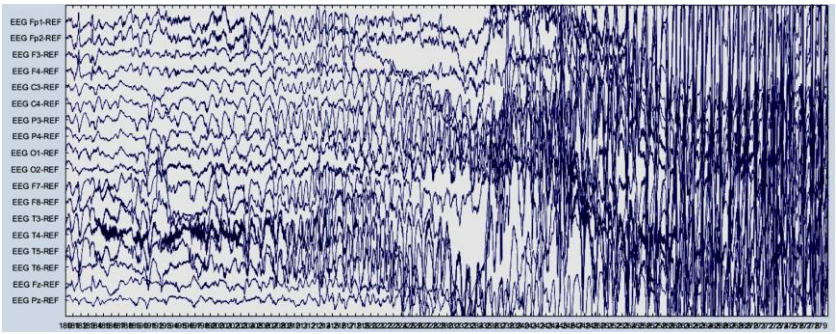
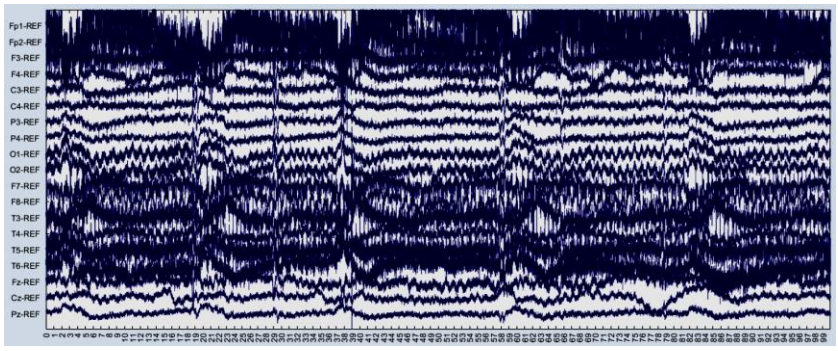


Figure 2. A Bipolar Montage EEG was Used in The Recording Process [24]

The EEG signal was recorded using a *NicOne* EEG amplifier with a sampling frequency of 256 Hz and using 19 electrodes positioned according to the standard 10-20 [25]. In addition, there is an electrode used as a reference in the middle section (Fz, Cz, Pz). Bipolar montage [26] is used in the recording process, and the electrodes used can be written as Fp1, Fp2, F3, F4, F7, F8, Fz, T3, T4, T5, T6, C3, C4, Cz, P3, P4, Pz, O1, O2 (Figure 2). The median recording duration for all patients is 74 minutes, 55.8 sec/patient and data were 30 seconds segmented/patient. Thus, the estimated number of samples is 7415 samples. EEG recorded data has European Data Format (EDF). EEG signal raw data examples for epilepsy and normal/non-epilepsy neonates are shown in Figure 3, where the y-axis is the electrode used and x-axis is the length of time of the recording process.



a) Epilepsy recording signal in neonates



b) Non-Epilepsy recording signal in neonates

Figure 3. Sample EEG signals for epileptic and non-epileptic neonates

Train/Test Data Split

After finishing with the last pre-processing stage, namely data normalization, the normalization results will be stored in CSV (Comma-Separated Values) format and will be used as input data for the classification stage. The data will then be split first before entering the classification stage with the CNN model. The data will be split into training data and test data using the *sklearn* (sci-kit-learn) module [27] in Python on Google Colaboratory. Therefore, we divide the data into 60% training data and 40% test data. This split proportion was chosen randomly as it is one of the simple techniques and is suitable for large datasets. The number of datasets used in this study is from 38 patient samples, thus, using the division proportion in the data split process, there will be 22 samples (60%) for training data and 16 samples (40%) for validation data. The data was segmented for 30 seconds from each recording of each patient. So, the total number of samples used was approximately 7415 samples.

Convolutional Neural Network (CNN) Algorithm Model

In this study, a 1D-CNN type is used. It consists of several convolutional layers, namely a pooling layer, a dropout layer, a flattening layer, and a fully-connected layer [28]. Each layer has three convolutional layers, three pooling layers (MaxPooling), three dropout layers, a flattening layer, and three fully-connected layers. The architecture of the CNN model used can be seen in Figure 4.

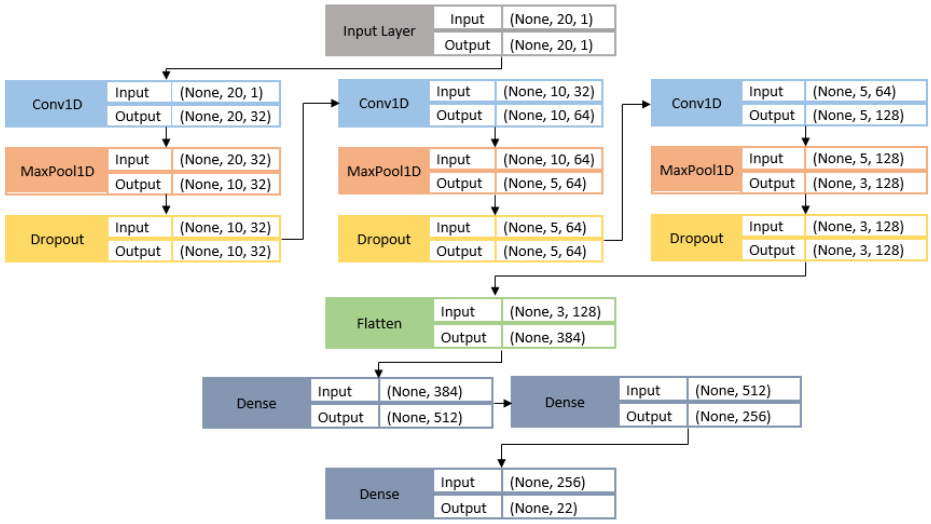


Figure 4. Process Flow of 1D-CNN Algorithm Architecture

The CNN architecture algorithm works from the start of the data input process. After the data goes through the splitting process, the data is input into the first group of layers consisting of convolutional layers, max-pooling layers, and dropout layers to produce a new feature map. The max-pooling layer plays a role in reducing the dimensions of the input which is useful for reducing calculations in the computational process. This process makes it more efficient. Meanwhile, the dropout layer is used to reduce overfitting during training. It will continue to the third group of layers. After that, the input data has a new feature map. This data will go to the flattening layer to be reshaped into a vector. Finally, the data will enter the fully-connected layer (dense layer) to be classified.

The CNN model used will be trained on each epoch. Epoch is a hyperparameter that will determine how many times the machine learning algorithm will work to process the entire training dataset. By training the model, we can quickly see when the network gets the best

accuracy for training data samples. From the model training results, the loss and accuracy values for each epoch are obtained sequentially from the training data and the loss and accuracy values in model validation.

Confusion Matrix

After finishing the training process on the CNN model, the next step is to evaluate the model used. The evaluation results will assess the model's performance in identifying epilepsy/non-epilepsy in the test data. In evaluating the model, a confusion matrix is used. This matrix will describe the number of correctly identified data and the number of incorrectly identified data in more detail.

From the confusion matrix, there are four value categories called True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These value categories will represent correctly and incorrectly identified epilepsy (seizure) or non-epilepsy (no seizure) data. The following terms are very important to understand the model evaluation results of the confusion matrix [28, 29]:

TP: The model correctly identified the data class as Epilepsy.

FP: The model incorrectly identifies the data class as Epilepsy.

FN: The model incorrectly identifies the data class as Normal/Non-Epileptic.

TN: The model correctly identifies the data class as Normal/Non-Epileptic.

The four main metric values used to evaluate a classification model are accuracy, precision, recall, and f1-score [28, 30].

Accuracy: is defined as a percentage of correct predictions.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

Precision: to predict how many samples are predicted as epilepsy is epilepsy. In other words, precision is the level of accuracy of the model in carrying out identification or classification.

$$precision = \frac{TP}{TP+FP} \tag{4}$$

Recall (Sensitivity): recall or sensitivity is a value that can see the ability of models to correctly identify or predict sample data or the model's success rate in identifying.

$$recall = \frac{TP}{TP+FN} \tag{5}$$

f1-score: is defined as a mean measurement of precision and recall. f1-score will be used when class distribution is asymmetric.

$$f1 - score = 2 \times \frac{recall \times precision}{recall + precision} \tag{6}$$

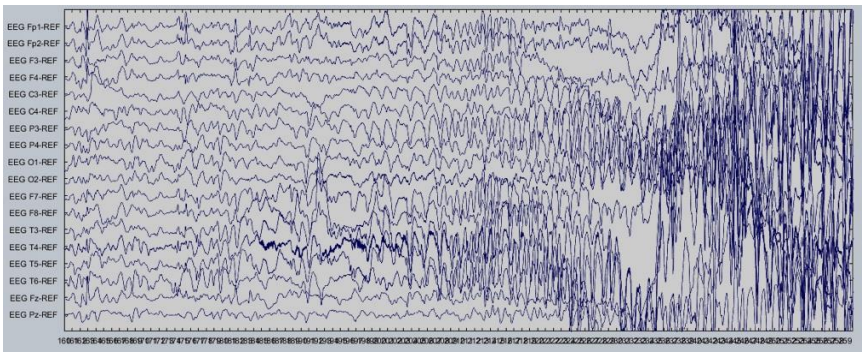
RESULTS AND DISCUSSION

Pre-processing Result

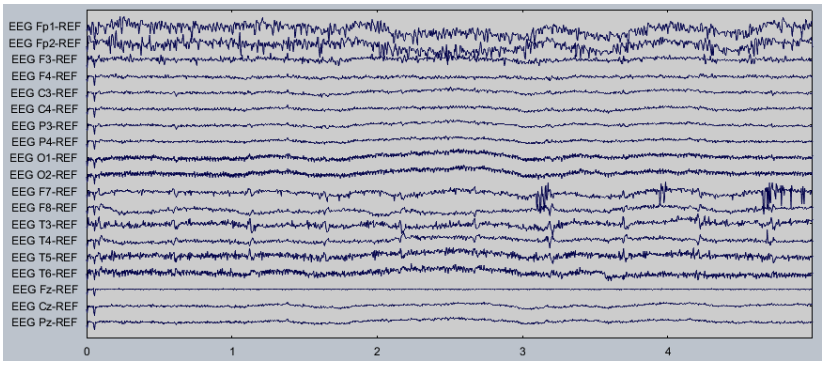
Before the data enters the classification stage, the data goes through the pre-processing stage first. The data used are the results of EEG recordings on 38 infants consisting of patients diagnosed with epilepsy (seizures) and non-epilepsy (no seizures). The methods used in this pre-processing are filter, segmentation, and feature extraction using the EEGLAB toolbox.

A Butterworth band pass filter with a cut-off frequency of 0.5 Hz - 70 Hz is used for data filtering. Filtering on EEG data is done to remove some noise/artefacts generated during the recording process, as the signals generated by EEG contain various important information. Thus, if the signal is mixed with noise/artefacts, the data or information on the signal will become unclear or even lost and will affect the results [31]. An example of filtering results on EEG data can be shown in Figure 5. This pre-processing stage will only be performed on two patients (EEG36/Epilepsy and EEG40/Non-Epilepsy), which are used as examples of data pre-processing.

From the filtering results, it can be seen that the filtered signal looks cleaner when compared with the raw data in Figure 3, but does not eliminate the information contained in the original data.



a) Filtration results in epilepsy patients (EEG36)

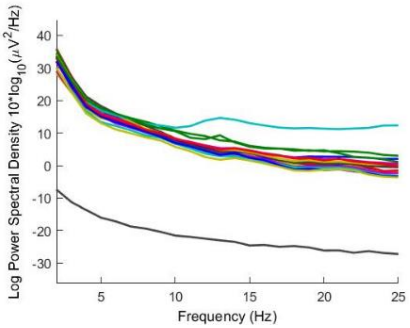


b) Filtration results in non-epilepsy patients (EEG 40)

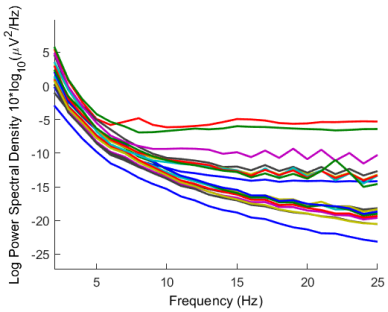
Figure 5. Example Filtering Results of EEG Data in Epilepsy and Non-Epilepsy with EEGLAB x-axis as the Recording Time and the y-axis as the Electrode Used

In the next stage, the data is segmented using the same software to be able to see more clearly which signals look like epilepsy and which are not. Then the data from the signal segmentation results will be Power Spectral Density (PSD) [32] calculated using Fast Fourier Transform (FFT) to get the signal characteristics on each EEG channel used. The results of the FFT are displayed with the energy or frequency spectrum shown in Figure 6.

The curve is the energy spectrum produced by each channel on the EEG. Then the results of the energy spectrum on each channel will be normalized using z-score normalization (Equation 2) for each signal on the channel as each channel on the EEG has its features. By normalization, the result of feature extraction will be a value with a range of 0-1. The value range is the minimum and maximum value of the feature, with 0 given for features on non-epileptic signals (no seizures), and 1 for non-epileptic signal features (seizures). To note, the x-axis is the frequency of each channel and the y-axis is the power spectral density value.



a) Frequency spectrum from an epilepsy patient (EEG36)



b) Frequency spectrum from a non-epilepsy patient (EEG40)

Figure 6. Power Spectral Density (PSD) Result

The frequency spectrum on each EEG channel in Figure 6 will produce spectrum values generated via the toolbox in EEGLAB-MATLAB. Power spectral density is a distribution of the frequency of a component. Therefore, upon analyzing the power spectral density (PSD) outcomes of patients with epilepsy and those without the condition, notable distinctions can be observed. The frequency distribution derived from individual channels of patients with epilepsy exhibits pronounced spikes or fluctuations and significantly higher logarithmic power spectral density (PSD) values (in dB) compared to non-epileptic patients. These findings indicate heightened brain activity within the epileptic group.

The spectral value of the PSD results through MATLAB in patient 36/EEG36 and patient 40/EEG40 can be seen in Table 1. The result indicates that there is non-stationary behaviour in the frequency domain.

Table 1. Frequency spectrum values of each signal in EEG36 and EE40 patients

Spectrum Value/ Channel	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
EEG36	1.15	1.58	1.79	1.89	-0.13	1.9	1.00	1.5	0.49	-1.06	0.26	0.81	0.25	0.62	0.68	0.97	2.01	1.37
EEG40	1.95	1.91	0.69	1.72	-0.63	-0.68	-0.53	-0.57	-0.29	-0.27	0.47	0.37	0.88	0.43	0.47	0.62	2.06	-0.58

The spectral values will serve as feature extraction and will undergo normalization prior to being utilized as input in the classification procedure. The normalization process will employ z-score normalization, facilitating enhanced data comprehension by the algorithm. As per Equation 2, the z-score normalization procedure necessitates the utilization of the mean value and standard deviation. The mean value represents the average of the EEG data (specifically, the spectrum value) across each channel, while STD corresponds to the root of the mean. Thus, there are mean values and standard deviation values that need to be known from the spectrum data to normalize it into binary (0/1) numbers that can be easily understood by the algorithm. The mean and standard deviation values from a spectrum of patient36/EEG36 are about 0.047313019 and 1.196074149. Meanwhile, in patient40/EEG40, the mean and standard deviation values show 0.021988304 and 1.0257269 respectively. The normalization process is also carried out for all patients in each channel.

Once these values are determined, the subsequent stage involves applying Equation 2 to normalize each utilized channel, thereby generating values within the range of 0 to 1, with "0" assigned to features that indicate signals of non-epilepsy and "1" assigned to features that

indicate signals of epilepsy. Consequently, the outcomes of the feature extraction process can be exhibited in Table 2, which showcases the normalized spectrum values.

The feature extraction results in Table 2 only show feature extraction on 2 patients, but in practice, feature extraction is done for all 38 patients. For the remaining patients, the same procedure is carried out; however, the results are not displayed due to the excessive volume of normalized data across each EEG channel for every patient. There are no explicit criteria for distinguishing epilepsy and non-epilepsy based on normalization results. However, considering that a value of "1" represents an epilepsy feature, while "0" corresponds to non-epilepsy features, an analysis of the extracted features from epilepsy patients reveals that they consistently exhibit maximum values during z-score normalization across multiple channels. This observation suggests that these patients can be categorized as having epilepsy based on this characteristic. The results of this feature extraction will be used as input to epilepsy (seizures) and non-epilepsy (no seizures) identification /classification systems using CNN.

Table 2. Feature Extraction Results in Each Channel EEG36 and EEG40 Patients

Patient/Channel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
EEG36	0	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	1	1
EEG40	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Model Training

After the data passes the modelling stage in Figure 4, the model is trained at each epoch. From the model training results, the loss and accuracy values for each epoch are obtained sequentially from the training data and the loss and accuracy values on the model validation. A graph of the model training accuracy value on training data and validation accuracy is shown in Figure 7.

From Figure 7, the training accuracy value is obtained from the training data and results in validation accuracy. The x-axis is the epoch or hyperparameter that will determine how many times the machine learning algorithm will work. The result accuracy value is 99.078% for training data and validation results were obtained at 82.069%. The obtained accuracy values serve as indicators of the model's ability to effectively learn from the provided data and feature extraction results.

There is also a loss value generated during the training of the model, as shown in Figure 8. This data will be used to see how bad the model is at learning the data. This results in a distinct loss values between the training loss and validation loss. The training loss yields a notably low value of approximately 0.0426%, whereas the validation loss demonstrates a result of approximately 1.0315%.

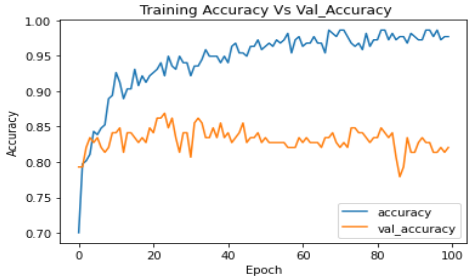


Figure 7. Training and Validation Accuracy Result

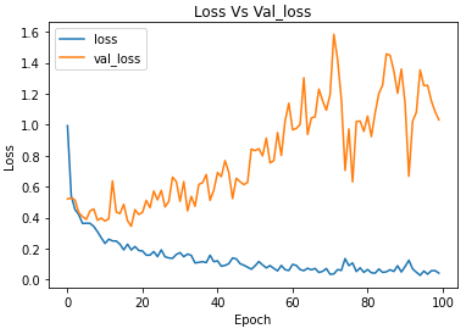


Figure 8. Training and Validation Loss Result

From both training results, it can be seen that the model can learn well from the data given. The training accuracy value generated in the training data has a higher value than the validation accuracy, which means the model is good enough to make predictions. This is due to the fact that the training accuracy value of the training data must have a higher value than the validation accuracy. However, when viewed from the loss value obtained, the validation loss value remains higher. Despite the inclusion of additional convolution layers and dropout layers in the model architecture, overfitting persists. This occurs due to the model's excessive reliance on the training data, which is attributable to the limited dataset available. Consequently, the accuracy value during validation diminishes as a result. Nevertheless, all things considered, the model performs satisfactorily, and the employed system algorithm effectively assimilates the data. In the realm of machine learning, an accuracy value of 80% or higher generally signifies a commendable model performance. Hence, based on this criterion, the model can be deemed as proficient [33].

Model Evaluation

Four value categories, namely TN, TP, FP, and FN, are obtained from the matrix in Figure 9. These value categories will represent correctly and incorrectly identified epileptic (seizure) or non-epileptic (no seizure) data.

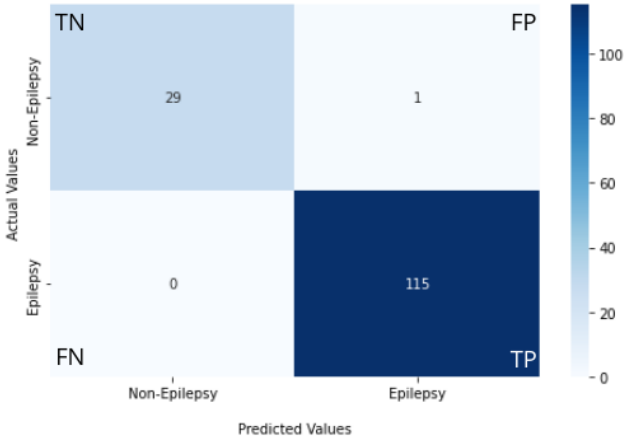


Figure 9. Model Evaluation Results from Confusion Matrix

In Figure 9, the amount of data identified by the model is generated based on the test data used. There are 115 data identified as TP, 29 data TN, 1 data FP, and 0 data FN from the total test data of 145 samples. These results enable the identification of data that has been incorrectly classified and falls into the FP category.

Then by generating the amount of data based on these four categories, we can measure the values that are usually generated by the confusion matrix itself, such as precision, recall or sensitivity, F1-score, and accuracy. These values can be calculated manually using Equations 3 to 6 or with the help of Python code such as the *sklearn* library [27]. These values are usually referred to as classification reports. The values of the classification report can be seen in Table 3.

Table 3. Classification Report Result

Class	Precision	Recall	F1-Score
Epilepsy	100%	97%	98.4%
Non-Epilepsy	99.1%	100%	99.5%
Accuracy			99.31%

From the classification report results in Table 3, several values are obtained that will be used to measure the predictive quality of the identification or classification algorithm used. There is precision, recall (sensitivity), F1-score, and accuracy values.

The precision value will explain the level of accuracy of a model in identifying or classifying data. It is known that the precision value for epilepsy (seizure) and non-epilepsy (no seizure) classes are 99.1% and 100%. Recall or sensitivity value explains the success rate of a model in identifying/classifying. From this study, the recall value for epilepsy (seizures) is around 97%, and for non-epilepsy (non-convulsions) is around 100%. The percentage results show that the recall value in the epilepsy (seizure) class is smaller than in the non-epilepsy (non-seizure) class. The results reveal instances of incorrect identification as the data is categorized within the FP class in the confusion matrix. In simpler terms, the number of FN values is smaller in comparison to the number of occurrences classified as FP.

Ideally, the model should exhibit zero occurrences of FP and FN across the dataset. From a clinical perspective, the presence of data classified as FP implies that further examinations are required for the patient, with the final diagnosis being determined after undergoing these additional tests. Conversely, data falling into the FN category indicates an improper diagnosis, resulting in the patient perceiving themselves as healthy and not pursuing treatment. However, if the number of FN instances becomes significant, it poses a risk as patients may delay treatment until the disease progresses severely. Therefore, in clinical practice, minimizing the number of FN cases is considered crucial, as excessively high FN values can potentially endanger the patient's life. Thus, FP results with the number of 1s in the confusion matrix are better than the 1s generated by the FN category [28].

The F1-score value for epilepsy (seizures) is 98.4% and for non-epilepsy (no seizures) is 99.5%. This provides information on the accuracy value that will describe how accurate the model is in identifying/classifying correctly. The accuracy results of this study are based on the results obtained through the confusion matrix. Result shows that the accuracy percentage is 99.31%. From the accuracy results, it can be concluded that the model proposed in this study produces accurate accuracy values and thus has high accuracy. Hence, it can be inferred that employing a simple machine learning model like 1D-CNN is adequate for classification and identification purposes, as demonstrated by numerous researchers. Furthermore, this study compares the accuracy of the model with that of previous research or studies to gauge its performance. Comparisons with other studies can be shown in Table 4.

Table 4. Comparison of the Model Accuracy with Some State-of-the-art Studies in This Field

Study	Dataset	Proposed Method	Accuracy
Elakkiya, R, et al,. [8]	NICU of Helsinki University Hospital	SVM, ANN, and CNN	95.99%
O'Shea, A, et al,. [6]	NICU of Cork University Maternity Hospital	Frequency Domain, Time Domain, Information Theory, SVM, and CNN	97.1% & 82.9%
Wei, et al,. [17]	Dept. of Neurology, Hospital of Xinjiang Medical University	2D Images input and long-term Recurrent CNN (LRCNs)	9.4%
Jana, GC. et al,. [18]	CHB-MIT Scalp	Spectrogram and 1D-CNN	77.57%
Sagga, D, et al,. [19]	CHB-MIT	VGGNET, ResNet and 1D-CNN	97.31% ~ 97.60%
T̈urk, O et al,. [34]	Bonn	Continuous Wavelet Transform and CNN	91.50%
Hassan, F et al,. [35]	Bonn	CNN and ML Classifier	96%
Proposed Method	NICU of Helsinki University Hospital	EEGLAB, PSD and CNN	99.31%

Numerous researchers have conducted studies on the identification and classification of epilepsy using the 1D-CNN method. From the comparison of accuracy results presented in Table 4, it can be observed that various methods and datasets utilized by other researchers have achieved commendably high accuracy levels. However, these methods may involve complex processes and extended time durations for identification. In contrast, this study aims to simplify the identification process by employing the EEGLAB Toolbox and 1D-CNN method, which despite its internal complexity, offers a more straightforward approach. Surprisingly, even with this simple methodology, the accuracy achieved is comparable to or even superior to other approaches. Although the increase in accuracy may not be substantial, the results of this study demonstrate considerable improvement compared to previous research endeavors.

This research can be enhanced by improving the pre-processing stage through a deeper understanding and utilization of the EEGLAB toolbox. This study's limitations stem from a lack of comprehensive knowledge regarding the optimal use of EEGLAB. Additionally, to further enhance the accuracy of the results, it is recommended to expand the dataset size and consider incorporating several layers into the 1D CNN. Furthermore, optimizing the data splitting process by proportionally dividing the data could potentially lead to improved validation performance. These proposed improvements would enhance the scientific value and applicability of this research. Moreover, similar approaches can be explored in future studies to address other diseases.

CONCLUSION

This research was conducted to find out how a 1D-CNN algorithm can be used to automatically classify multi-channel EEG raw data. The 1D-CNN model with multiple layers

was used to classify epileptic (seizure) and non-epileptic (non-seizure) states. The raw data goes through the pre-processing stage first using EEGLAB, and then the CNN model is trained to determine the performance of the 1D-CNN model. The ensemble model provides a training value of about 99.078%. Also, the model is evaluated using a confusion matrix and produces an accuracy of 99.31%. This study provides compelling evidence that the utilization of a simple 1D-CNN algorithm is highly effective and efficient for the automatic classification of epilepsy.

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AUTHOR CONTRIBUTIONS

Izaz Nadyah: Conceptualization, Methodology, Software, Investigation, Data Curation, Writing - Original Draft, Review & Editing, Visualization; Khoerun Nisa Syaja'ah: Conceptualization, Validation, Formal Analysis, Writing – Review & Editing, Supervision, Project Administration; and Mada Sanjaya WS: Conceptualization, Validation, Supervision, Project Administration

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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