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Emotion Recognition of EEG Signals Using Wavelet Filter and Convolutional Neural Networks

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Emotion Recognition of EEG Signals Using Wavelet Filter and Convolutional Neural Networks

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Abstract—Emotion is a psychophysiological process that is triggered by conscious or unconscious states. Emotional information in the human brain can be captured through a multi-channel Electroencephalogram (EEG). EEG signals are recorded from multiple channels, representing information points of electrical activity from different parts of the brain. While the EEG signal of each channel is a sequence, some studies use one dimension in recognizing patterns, and the signal from the next channel is a continuation of the sequence from the previous channel. It makes the channel sequence less maintained so that the EEG signal processing from multi-channel is seen as a matrix, i.e., the vertical direction is the signal from various channels. While the horizontal direction of the sequence of each channel. So that the signal processing of the multi-channel is rich in information in the appropriate order, this study used 2D Convolutional Neural Networks (CNN) for emotion recognition, with various architectures and configurations to get the best performance. In addition, the EEG signal needs to be extracted, which reflects the emotion variable first using a Wavelet. That is the 4-45 Hz frequency band of Theta, Alpha, Beta, and Gamma. The results show that two-dimensional CNN, which pays attention to signal order, produced the best accuracy of 83.44% compared to 75.97% with one-dimensional CNN. Experiments gave the best configuration used eight layers and Stochastic Gradient Descent (SGD) weight correction.

Keywords—emotion recognition, EEG signal, Wavelet, CNN, multi-channel

I. INTRODUCTION

Emotion is a psychophysiological process that is triggered by a conscious state or not. Emotions correlate with human personality, interests, and health [1]. The emotions are divided into positive, neutral, and negative emotions. Positive emotions are good for mental health, while excess negative emotions can be destructive. One of the causes of mental health disorders is depression [2]. Someone who is depressed finds it difficult to control emotions, so therapy is needed. Therefore, emotional identification and therapy monitoring more positively are important [3]. This monitoring can be used physiological signals with an Electroencephalogram (EEG) device, reflecting human brain activity [1].

EEG can be used to diagnose several neurological disorders and emotional classifications [4] and a method of electrophysiological monitoring of the electrical activity of the human brain [5]. The recognition of emotions signal-based EEG is still very challenging to the study at this time. EEG signaling is considered the most reliable technique for emotion recognition because of its non-invasive nature [6]. Previous research has identified emotions when listening to music in two dimensions of emotion: arousal and valence [7]. Another study identified emotions in three classes of Chinese films: positive, neutral, and negative [8].

The feature extraction process in emotion recognition is important because it helps obtain the required emotion variable information. Previous studies identified four emotions: happy, sad, angry, and relaxed by applying Theta (4-8 Hz), Alpha (8-12 Hz), Beta (12-30 Hz), and Gamma (30-45 Hz) waves to achieve accuracy by 92.01% [9]. Another study extracted EEG signals in the 1-50 Hz frequency using Delta, Theta, Alpha, Beta, and Gamma waves with increased accuracy of 7.25% - 13.40% [10]. Also, the EEG signal at a frequency of 0.3-50 Hz is filtered to filter noise in classifying positive, neutral, and negative emotions [11]. Beta and Gamma frequency bands can be relied on to recognize emotions from EEG signals. In the previous studies [12], positive emotions increased Beta and Gamma band, neutral and negative have low Beta and Gamma, and neutral has an increased Alpha.

In addition to using a series of waves to obtain information on emotional variables, it can be done by filtering specific frequencies. Previous research performed a filter for extracting positive, neutral, and negative emotional EEG signals in the frequency range 4-45 Hz, resulting in an accuracy of 96.77% [13]. One method that can be used to filter non-stationary signals such as EEG signals is Wavelet. As in previous studies [5], a Wavelet filter was applied from 4-45 Hz to classify four emotion classes: happy, angry, sad, and relaxed.

Identification of emotions through EEG signals can be made by various methods, one of which is Convolutional Neural Networks (CNN). CNN has one, two, or multi-dimensional types. Previous research used two-dimensional CNN (2D CNN) for the emotional classification of EEG signal images in two classes (high and low) and three classes (high, average, and low) based on arousal and valence dimensions, respectively, with a 2D array as input [14]. Also, classification of EEG signals from topographic images in three emotional dimensions: arousal, valence, and dominance, converting time series into 2D images [15]. Another study used the DEAP and SEED datasets to identify emotions with an accuracy of 82.84% and 90.59%, respectively [16], and using the DEAP dataset with the 2D CNN method to identify two dimensions of emotion, arousal, and valence, with an accuracy of 72% and 71%, respectively [17].

EEG is sequential data. Therefore the feature extraction process must maintain signal order. Besides identifying, CNN can also perform extraction while maintaining the order of the signal, which is carried out spatially-temporal with the vertical dimension in channels, while the horizontal dimension is in the form of times. The previous study recognized EEG signals in each channel using the Parallel Sequence-Channel Projection Convolutional Neural Network in two emotional dimensions with 95.96% and 96.24% [18]. Another study selected 12 out of 32 EEG channels that used 2D CNN to increase the accuracy by about 20% on average [19]. Also, other studies have handled the order of data in the classification of valence and arousal emotions using the Temporal Convolutional Network with an accuracy of 74.4% and 71.4%, respectively [20]. Different from previous studies, processing images from recorded EEG signals have a longer computation time. Meanwhile, this study used pure signal, which is expected to increase accuracy and decrease computation time.

This study proposed a Wavelet filter to extract EEG signals into the 4-45 Hz frequency range containing Theta, Alpha, Beta, and Gamma waves. The extraction results were identified in three emotions classes using Convolutional Neural Networks.

II. METHODS

The identification of emotions through EEG signals is shown in Fig. 1. Wavelet filters are used to obtain a frequency range of 4-45 Hz through the decomposition stage. Meanwhile, CNN identifies one of three classes of emotions: positive, neutral, or negative.

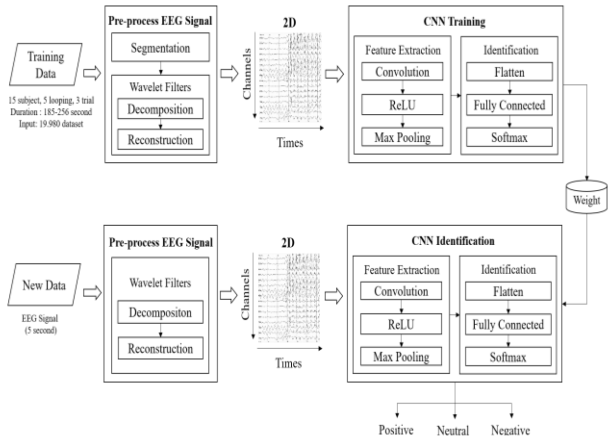

Fig. 1. Identification of emotions using Wavelet filter and CNN

A. Dataset

EEG signal data was obtained from the SJTU Emotion EEG Dataset (SEED) [12] of 15 subjects (seven male and eight female). Each subject watched 15 Chinese film clips, which fit into three emotions: positive, neutral, and negative classes. The sampling frequency of the EEG signal is 1000 Hz which is reduced to 200 Hz with a duration of 185-265 seconds.

This study used 12 channels, namely FT7, FT8, T7, T8, C5, C6, TP7, TP8, CP5, CP6, P7, and P8, which are considered more effective 62 channels [10]. In total, there are 675 datasets. The duration used is 185 seconds, which are then segmented into 5 seconds [21]. It results in 37 x 675 or 24.975 datasets.

B. Wavelet Filter

A signal that is filtered at a specific frequency helps distinguish emotional states. Wavelets can be used to filter signals in a frequency of 4-45 Hz. Wavelet filters to obtain signal frequency information in a specific time unit with two main processes: decomposition and reconstruction. Decomposition is the process of extracting the signal into a particular frequency, while the reconstruction is returning the extracted signal to its original form [22]. In decomposition, the original signal's convolution process used the dot product operation with the kernel. The basic Wavelet function is shown as (1). Where n is the data length, σ is the scale variable, and τ is the translation variable.

$$\psi_{\sigma,\tau}(n) = \frac{1}{\sqrt{|\sigma|}}\,\psi\left(\frac{n-\tau}{\sigma}\right) \qquad (1)$$

The Wavelet decomposition function consists of several approximation and detail steps (2) and (3). Where k is the data index, $g(2k-n)$ is the approximation coefficient (low-pass filter), $h(2k-n)$ are the detail coefficient (high-pass filter) and $x(n)$ is the nth value.

$$y_{low}(k) = \sum_n x(n).\,g(n-k) \qquad (2)$$

$$y_{high}(k) = \sum_n x(n).\,h(n-k) \qquad (3)$$

The previous study used Wavelets to retrieve information from an emotional variable, increasing accuracy from 72% to 87% [3]. Another study used wavelets to identify emotions that resulted in 91.3% and 91.1% [23]. Wavelets have various coefficients, such as Daubechies (db), Discrete Meyer (dmey), Haar (haar), Symlets (sym), and others [24]. The previous study used Daubechies4 Wavelets to extract EEG signals into waves representing motor imagery and emotions [22].

The decomposition process is carried out to obtain the frequency component in the range 4-45 Hz using the Daubechies4 wavelet coefficient. The original signal of each segment is convoluted to the kernel. A sampling frequency of 200 Hz allows signal information to be in the range of half or 1-100 Hz (the Nyquist frequency) [24]. The Wavelet decomposition process is illustrated in Fig. 2.

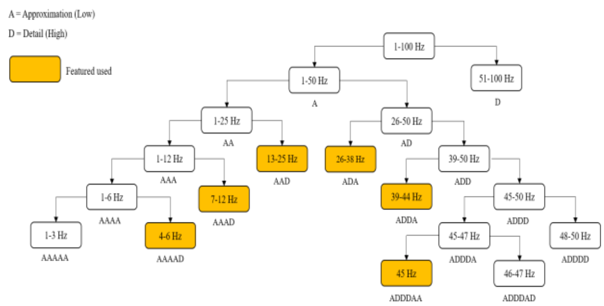

Fig. 2. Process signal filter using Wavelet

TABLE I. AMOUNT OF THE DATA AFTER WAVELET FILTER

Frequency	**Amount of the Data**	
	1 Channel	**12 Channels**
4-6 Hz	30	360
7-12 Hz	61	732
13-25 Hz	131	1.572
26-38 Hz	131	1.572
39-44 Hz	61	732
45 Hz	10	120
Total	**424**	**5.088**

Based on Fig. 2, the decomposition process consists of six stages with several approximation steps and details using (2) and (3), so that 424 data points are obtained for each channel. The result of the Wavelet filter process can reduce 12.000 to 5.088 data points in 12 channels. Table I shows the results of the EEG signal extraction using the Wavelet filter.

C. Convolutional Neural Networks

Convolutional Neural Networks (CNN) is a method in machine learning with several types: one-dimensional, two-dimensional, or three-dimensional. CNN is also known as deep learning, which automatically classifies signals [25]. CNN consists of a feature extraction and classification layer that works like the eye by seeing the condition for a moment without remembering the previous information. The feature extraction is carried out by the convolution and pooling layers, while the classification task is managed by the fully connected layer [9]. The model applied in this study is a two-dimensional CNN (2D CNN). The 2D CNN architecture is shown in Fig. 3.

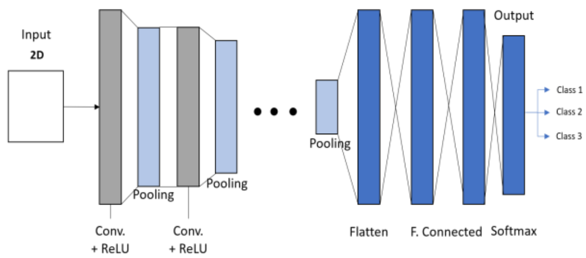

Fig. 3. Two-dimensional CNN architecture

CNN performance is highly dependent on hyperparameters. Meanwhile, better accuracy can be achieved with fewer parameters and less complexity [9]. This stage takes advantage of the Wavelet filter signal data from 12 channels that enter the feature extraction stage. Then enter into the identification stage by CNN with a two-dimensional architecture. This study used eight layers with five convolution layers, three layers of max pooling, and three layers of identification.

a) Convolution (Feature Extraction) Layer

Convolution is a layer for converting input data using dot product operations with filters or kernels to produce feature map values. Previous research used a convolution kernel of 3x3 to identify emotions [14]. In this study, we construct a two-dimensional (2D) data structure. Each represents the wavelet energy distribution in spatial-temporal features with the vertical dimension for channels and the horizontal dimension as time sequences. The network utilizes a convolution kernel filter of 3x3 with one stride to handle the EEG signal on each channel. The configuration of the EEG signal as a matrix can show the vertical direction as multi-channel and horizontal as the time sequence of the signal for each channel, making the signal from one channel connected to other channels at the same time and the previous time signal on the same channel simultaneously.

The convolution process produced smaller dimensions of input the data. Meanwhile, so that information is not lost, the convolution result can be manipulated using padding by adding zero values to the pixels on each side of the input. The 2D convolution function is shown in (4).

$$C[m,n] = \sum_{u}\sum_{v} A[m+u, n+v] \cdot B[u,v] \qquad (4)$$

Where every element $C[m,n]$, obtained from multiplying one element A with one kernel element B then added. While the function to calculate the number of feature maps is as follows (5).

$$output = \frac{N-F+2P}{S} + 1 \qquad (5)$$

N represents the input width, F represents the filter or kernel width, P is the padding, and S is the stride. Convolution operations are combined with activation functions to increase non-linearity in the network [25]. The most commonly used activation function is the Rectified Linear Unit (ReLU) to convert all negative values to zero. If the input value of the activation function is positive, then the output of the neuron is the value of the activation input itself.

b) Max Pooling Layer

Max Pooling is a layer used to reduce the number of parameters and computations in the network and control overfitting [14]. Max pooling is after the convolution layer. The output of the Max Pooling process is a matrix with smaller dimensions on the feature map. The Pooling layer works independently of each slice of the input depth and resizes it spatially using the max operation.

Previous research used Max Pooling with a size of 2x2 and stride two for the three-dimensional classification of emotions [15]. In this study, the Max Pooling size used was 2x2 with two strides. This extraction process can reduce from 5.088 to 52 data points calculated using (5). The results of the extraction process can be seen in Fig. 6.

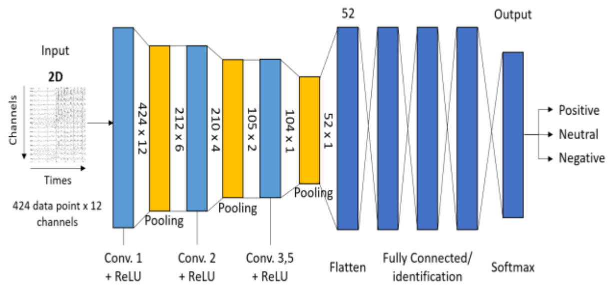

Fig. 4. Feature extraction and identification of 2D CNN

c) Identification of Layer

The identification layer comprises fully connected neurons or fully connected to the Multi-Layer Perceptron (MLP) architecture. MLP consists of an input layer, a hidden layer, and an output layer. The previous study used a Support Vector Machine (SVM) in the identification layer [26].

At the identification stage, a classification method used the Backpropagation algorithm to update weights during training [27]. Backpropagation works to achieve the minimum error value between predicted and actual results with the backward propagation process. The error value is obtained from the Feedforward stage with a progressive propagation process. When the process is carried out, the neurons will be activated using the activation function. MLP architecture can be seen in Fig. 5. Where X is the input unit resulting from the feature extraction process, or 52 units. Y is the hidden neuron so that 12 units are obtained, and Z is the output unit with three units that adjust to the number of classes. After completing the previous two steps, flattening is applied to convert the original value in a matrix into a vector as input to the fully connected layer.

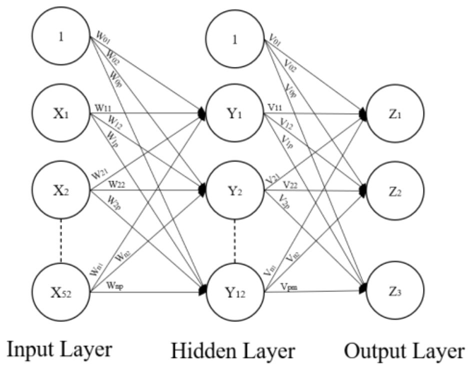

Fig. 5. Multi-Layer Perceptron architecture

In Backpropagation, there is an activation function that is used to determine the output of a unit. In general, CNN used the Softmax activation functions. The Softmax activation function calculates the probability value as a determinant of each target class [15], producing accuracy. Accuracy is the amount of data that is correctly identified. In addition, there is a way to minimize the difference between the target and the computational output using a Loss Function or Loss at the identification layer. One of the Loss Functions that can be used is Cross-Entropy to optimize network parameters by (6) [28]. Where C is the number of class labels, t_i is the actual or supposed value, and S_i is the result of the Softmax value.

$$Loss = -\sum_{i}^{C} t_i \, log(S_i) \qquad (6)$$

III. Result and Discussion

This research performs an EEG signal filter used Wavelet in the frequency range 4-45 Hz. It is then split from 24.975 data sets into 80% or 19.980 data sets used for training, while 20% or 4.995 data sets are used for testing. The 12 channels used include FT7, FT8, T7, T8, C5, C6, TP7, TP8, CP5, CP6, P7, and P8. The Wavelet reduces signal from 12.000 to 5.088 data points for each channel. The results of the wavelet filter are used as input in the identification of EEG signals used in the 2D-CNN method into three classes, namely: Positive, Neutral, and Negative.

A. One-dimensional and Two-Dimensional CNN

In this study, the first experiment was conducted to measure the use of one- and two-dimensional CNN types. The results are shown in Table II.

TABLE II. Comparison of 1D CNN and 2D CNN

Methods	Accuracy %	Loss	Time (s)
One-dimensional CNN	75.97	1.277	0.2406
Two-dimensional CNN (proposed method)	83.44	0.769	0.1111

In Table II, the two-dimensional CNN (2D CNN) method produces a better accuracy rate of 83.44% than the one-dimensional CNN (1D CNN) with an accuracy of 75.97%. This study used a two-dimensional data structure representing the spatial-temporal features of a multi-channel EEG signal, with a vertical dimension in the form of channels and a horizontal dimension in the form of time. The proposed method utilized a convolution filter with a size of 3x3 so that the signal sequence is maintained. 2D CNN method decreased in Loss from 1.277 to 0.769 and has a much faster computation time. In previous studies, the 2D convolution kernel has more parameters to learn and requires more time to practice [29].

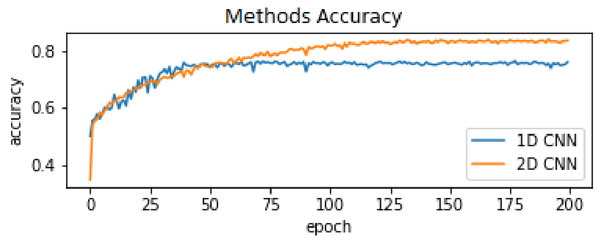

Fig. 6. Accuracy value comparison of 1D and 2D CNN

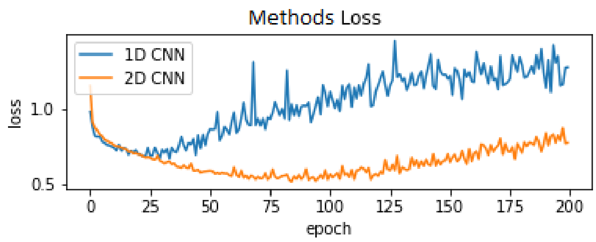

Fig. 7. Loss value comparison of 1D and 2D CNN

In Fig. 6, the accuracy starts to stabilized around the 120th epoch. 2D CNN had a transient stated that is long enough to achieve stable accuracy but produced high accuracy. While using 1D-CNN fluctuated at the beginning and stabilized around the 40th epoch. Compared to 2D CNN, 1D CNN has a much faster reach steady-state but results in lower accuracy. Meanwhile, Fig. 7 shows the very fluctuating Loss results in the 1D CNN method compared to the 2D CNN method. Loss value on the use of 2D CNN around the 25th epoch shows convergence to the 100th epoch. The Loss value then continues to increase but still maintains accuracy.

B. Layers Optimization

Subsequent experiments were carried out to determine the level of accuracy and better Loss on the use of four, eight, and 16 layers of CNN. Experiments used two different optimization models: Maximum Adaptive Moment Estimation (AdaMax) and Stochastic Gradient Descent (SGD). They were using 200 epochs with a learning rate of 0.0100. The experimental results are shown in Table III.

TABLE III. Comparison Between Layers Optimization

CNN Layers	Optimization Models			
	Accuracy %		Loss	
	AdaMax	SGD	AdaMax	SGD
4	78.67	78.73	0.950	0.946
8	77.73	**83.44**	2.034	**0.769**
16	79.72	75.95	0.941	1.043

As seen in Table III, eight layers with SGD weight correction resulted in the best accuracy of 83.44% and the lowest Loss of 0.769. However, using eight layers with AdaMax resulted in low accuracy and high Loss compared to other Loss. Meanwhile, using four layers with AdaMax and

SGD produces almost the same accuracy but produces quite a good accuracy and Loss compared to eight layers with AdaMax. Meanwhile, when using 16 layers with AdaMax, it produces better accuracy than other than eight layers with SGD, but when using SGD, it gives the lowest accuracy compared to another accuracy. In this experiment, layer selection and weight correction models were almost the same.

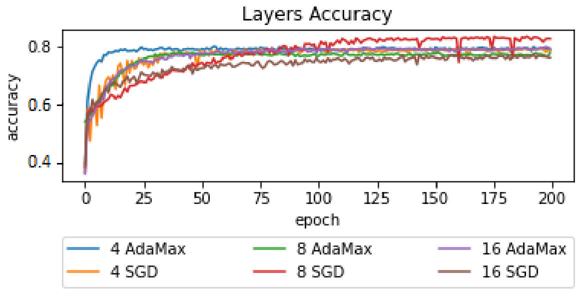

Fig. 8. Accuracy value comparison of layers CNN using AdaMax and SGD

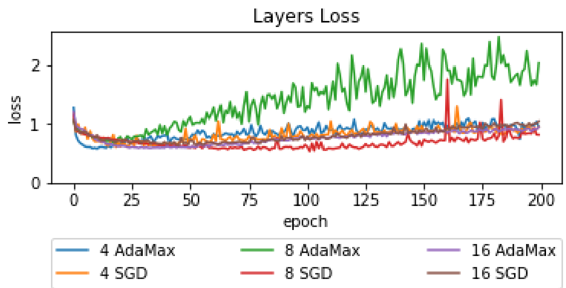

Fig. 9. Loss value comparison of layers CNN using AdaMax and SGD

At the start of the training, eight layers with SGD weight correction showed slow transients but resulted in higher accuracy, as in Fig. 8. Accuracy starts to stabilize around the 125th epoch for all layers. The accuracy of the four, eight, and 16 layers with SGD tends to fluctuate because SGD updates the weights by taking random values for each training data. Meanwhile, AdaMax tends to be faster reached steady-state but shows low accuracy because AdaMax is an algorithm with adaptive learning. In addition, the SGD with eight layers showed a more significant change in Loss value at the beginning of the learning towards convergence at the 125th epoch, as in Fig. 9. Meanwhile, AdaMax, with eight layers, has high Loss and fluctuates compared to other Loss values.

C. Parameter Optimization

This experiment used eight layers which are compared with the SGD model and different parameters. Learning rates of 0.0001, 0.0010, and 0.0100 are applied to get better results. The experimental results can be seen in Table IV.

TABLE IV. COMPARISON USING DIFFERENT LEARNING RATE

Learning Rate	Accuracy %	Loss
0.0001	79.26	0.893
0.0010	80.06	0.906
0.0100	**83.44**	**0.769**

In this experiment, using a learning rate of 0.0100 can provide better accuracy and Loss values. Meanwhile, at a learning rate of 0.0010, it produces a higher Loss value but produces a good accuracy than a learning rate of 0.0001. So, we can adjust the learning rate value, which can provide a convergence of Loss value. The most optimal results were obtained in this study, using the two-dimensional CNN method on the SGD optimization model with eight layers and a learning rate of 0.0100. The graph of accuracy and Loss values on the effect of learning rate can be seen in Fig. 10 and Fig.11.

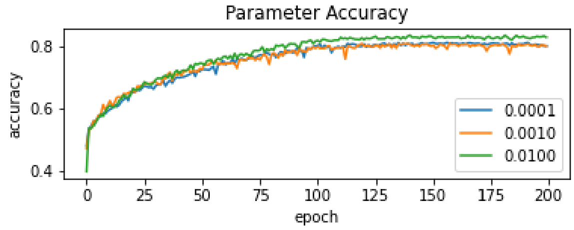

Fig. 10. Accuracy value comparison of learning rates

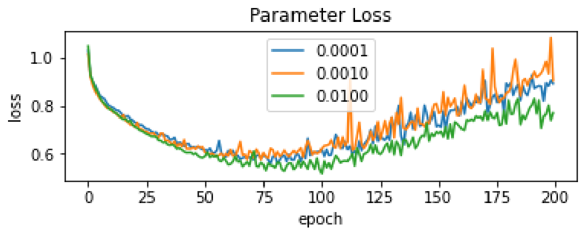

Fig. 11. Loss value comparison of learning rate

As seen in Fig. 10, a learning rate of 0.0100 produced higher accuracy than other learning rates. Meanwhile, the learning rates of 0.0001 and 0.0010 show a slight difference the accuracy. All learning rates also show transient states that tend to take a long time to achieve stable accuracy. At the beginning of the training, the accuracy continued to increased until it passed the 100th epoch and looked stable at the 125th epoch. In Fig. 11, a learning rate of 0.0100 also results in a better loss value. On the other hand, the Loss value in all learning shows fluctuating results and converges at the 100th epoch.

D. Comparing with the Others Methods

This study compares the proposed method with previous research in feature extraction that pays attention to data sequences, as shown in Table V.

TABLE V. COMPARISON WITH THE OTHERS METHODS

Methods	Accuracy %
2D CNN (proposed method)	83.44
Temporal Convolutional Network [20]	74.4 and 71.4

The results show that the model built in this study produces higher accuracy than research [20]. It showed data characteristic was significant in recognition performance. However, it is worth comparing that combining signals from several channels with one vector gives poor results. In contrast, this study used two-dimensional CNN so that the signal sequence of each channel is maintained.

E. Compare The Previous Methods of the Same Datasets

Several previous studies used the SEED dataset with different methods for identifying emotions, as in Table VI. As seen in Table VI, the model built in this study resulted in better accuracy than the previous study [10] [30]. Research [28] has slightly higher accuracy because the multi-channel EEG signal is converted to an image, thus requiring a longer computational time. Meanwhile, this study used CNN from a multi-channel EEG signal matrix to save one stage in signal processing compared to that research.

TABLE VI. COMPARISON WITH THE SAME DATASET AS THE PREVIOUS RESEARCH

Methods	Accuracy %
2D CNN (proposed method)	83.44
Maximum Independence Domain Adaptation (MIDA) [10]	72.47
CNN [28]	84.35
Recurrent Neural Networks-Long Short Time Memory (RNN-LSTM) [30]	80.00

IV. CONCLUSION

EEG signal processing from multi-channel using two-dimensional Convolutional Neural Networks (CNN) can capture much information from electrical activity in the brain, especially emotional variables, with signal sequences that can be maintained. So that signals from different channels simultaneously can be related to each other if treated as a matrix using CNN. It is evidenced by an increase in accuracy of about 8% compared to all channel EEG signal processing translated into vectors. Although the multi-channel EEG signal can be converted as an image first, it will undoubtedly impact the swelling of the computation time. In addition, EEG signal extraction is necessary to make it easier for CNN to recognize emotional information as a classification variable. The combination of Theta, Alpha, Beta, and Gamma waves is the optimal configuration for emotion recognition, carried out with Wavelets.

In addition, emotion recognition needs to adjust the configuration and architecture to improve accuracy. Eight CNN layers with the SGD weight correction model are more optimal than AdaMax and other layers. In addition, the use of a learning rate of 0.0100 can provide higher accuracy than other learning rates. Further research needs to perform random convolutions so that the signal relations between channels can be more helpful in distinguishing classes and modifying the method so that the relationship between sequences will increase the performs.

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