Stroke severity classification based on EEG signals using 1D convolutional neural network

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Abstract. Acute Ischemic Stroke (AIS) is one kind of stroke that occurs the most. Stroke itself is the number one cause of death that can reduce blood flow and deprive the oxygen into the brain. Early diagnosis can help patients getting faster medical treatment thus avoid unwanted damage to the brain. Electroencephalogram (EEG) is an alternative tool for diagnosing AIS to the standard tools as in MRI or CT-scan. In this research, we try to classify stroke severity with 1 dimensional CNN (Convolutional Neural Network). The proposed method calculates the power spectral density (PSD) of EEG recordings from normal and stroke subjects, as the model’s inputs and extracts feature automatically using CNN. The final feature-maps were trained in fully connected layer to classify 4 classes: normal, mild, moderate and severe stroke. The research is conducted to reach the possible optimum computing time with accuracy reached to 97.3% for 64 s segmentation, and 50 convolutional filters with 1x120 kernel size. This result is obtained by using the EEG signal from 4 channels: C3, C4, O1, and O2.

1. Introduction
Stroke is an uncommunicable disease that has globally become one of the leading causes of death. In Indonesia, it is the most cause of death, premature death, as well as death and disability combined as reported by The Institute for Health Metrics and Evaluation (IHME) in 2017. There are two types of stroke, ischemic and hemorrhagic. The acute ischemic stroke (AIS) has more than 80% incidence. AIS occurs when a clot or other blockage blocked the way within an artery leading to the brain, thus reduces the blood flow and deprives the oxygen into it.

An early prognosis is required in order to minimize the unwanted impact for the patients. The standard diagnose tool often used are Computed Tomography (CT-Scan) and Magnetic Resonance Imaging (MRI) which can give quiet accurate results. Even though performed in the safest procedures, there are still some small potential risks concerning the X-ray exposure to the patient body. In Indonesia the availability of the tools itself is still limited in large hospitals due to very expensive cost needed to use and maintenance. Moreover, both tools may take several hours to get the result while the critical first aid sometimes needs quicker action [1].

For community hospitals need alternative diagnostic tool as offered by CT and MRI. The propose alternative is to use Electroencephalogram (EEG) which is safer, more affordable. EEG captures the brain signals using its electrodes mounted to the head of the patient non-invasively. These electrical signals captured by the electrodes are produced by the activities of the human brain.
Using the brain wave signals, we intend to detect the ischemic stroke patient since the Cerebral Blood Flow (CBF) in stroke patients is altered from normal patients. Normally, CBF value ranges between 50 - 70 mL · 100 g⁻¹ · min⁻¹ and decreases to 25 - 30 mL · 100 g⁻¹ · min⁻¹ in ischemic stroke patients [2]. These changes are related to the EEG signals directly by the decreasing of the fast wave activities like beta and alpha frequencies and increasing the slow wave of delta and theta frequencies [1].

Some studies are conducted to see the pattern of these signals in regard of classifying ischemic stroke and non-stroke patients, for examples Omar et al. had used Relative Power Ratio (RPR) delta, theta, alpha and beta to cluster three stroke levels [3], Putten had found out that there was a positive correlation between Brain Symmetry Index (BSI) and the National Institute of Health Stroke Scale (NIHSS) scores [4], Finnigan et al. had used QEEG and measure Delta/Alpha Ratio (DAR), relative alpha power and found that each measures are correlated with NIHSS score [5], Osimalina had used DAR, DTABR and BSI combined [6], with the same features Fitriah added Principal Component Analysis to increase the accuracy with a less number of channels [7]. Mostly those researches conducted with handcrafted features which need to be extracted first with expertise domain knowledge. In this study, classifying task would be performed without the handcrafted features and the learning process was done by one of the deep neural network methods i.e. Convolutional Neural Network (1D-CNN).

Deep learning is a state-of-the-art machine learning (ML) approach which automatically encodes hierarchy of features and are adapted to the data [8]. This capability allows the model to learn only from ‘raw’ data. One of the most widely used types in deep learning is CNN [1]. In recent years CNN has an outstanding success in the field of computer vision since its ability to extract local feature in neighboring element in the input data where the same patterns may occur in different places. The use of filter kernel can reduce the numbers of learnable parameter to the size of kernel and is independent of the input data, whereas in the case of ordinary shallow neural network the parameter would increase as the input size getting bigger.

Not only implemented in image data, CNN model can be constructed on 1D data e.g. EEG signals. There are some studies related to 1D-CNN for EEG data, for example, automatically sleep stages scoring [9], features extraction for classifying epilepsy [10], automated detection and diagnosis of seizure [8], and ischemic stroke identification [11].

2. Method
This study used the EEG data from previous researches [6], [7], [11] which were obtained from 31 normal subjects and 27 patients with an acute ischemic stroke. The data were taken by the Pusat Otak Nasional (PON) or National Brain Center Hospital in Jakarta using 2 different tools, Xltek for some data and Biologic for the rest. As for the sampling rate, acquisitions were done in 512 Hz sampling rate, except for a few subjects where a 256 Hz sampling rate was used instead. Recording of EEG data took time approximately 30 minutes for all patients with electrode placement according to the International 10-20 system and were stored in European Data Format (.edf file). From several channels provided, we limited to choose only 4 channels C3, C4, O1 and O2 based on the channel reduction research conducted using PCA by Fitriah [7].

The CBF of acute ischemic stroke (AIS) patients normally declines from the non AIS subjects, thus causing the slower wave frequencies such as delta and theta to emerge followed by the loss of higher frequencies such as beta and alpha [1]. This phenomenon can be easily identified from the frequency analysis of the EEG rather than from the time domain analysis. Since EEG signals happen to be stochastic process, the spectral analysis is better to use the power spectral density (PSD) which is kind of averaging the signal rather than a simple FFT.

There are many PSD estimation methods can be used. In this study we used the Welch method where its main advantage is the robustness that the estimated PSD would not contain any invalid frequency peaks, while its drawback is due to the process of windowing that would lead to distortion of resulting PSD. Welch method mainly comprises of these steps: dividing signals into multiple overlapping sections, taking periodograms of each section, and then averaging periodograms to obtain spectral estimates. The length of the window used in segmentation affects the frequency resolution, so the wider
window yields narrower frequency peak accordingly. Four bands of frequency that come to interest in this study is in the range below 20 Hz, hence we downsample the 512 Hz to 32 Hz so the computational complexity could be reduced. Welch’s PSD is calculated with 64 window length and 50% overlap. The estimated PSDs as so-called ‘raw inputs’ are then passed on to the CNN model.

In order to have large number of inputs, before calculating the PSD 1 subject’s EEG is divided into several parts with shorter duration and equal length. This duration per segment is then varied to find the optimum length that yields the best accuracy. The new inputs after segmentation are then split into 80% training set and 20% testing set. The schematic of preprocessing step can be seen in Figure 1.

The novelty of this method compared with the previous studies is that features are extracted automatically through the learning algorithm and not derived from manual calculations where some domain knowledges are necessary. The feature extraction and classification stage are both done in the CNN architecture. Layers in CNN mainly consist of convolutional layers (CL) with 50 filters and 1x120 kernel size, pooling layers (PL) with scaling factor of 1/2, and fully connected (FC) layers consecutively. The training would be conducted for about 300 epochs. For visualization, the architecture of the CNN with 1 CL and 1 PL is shown in Figure 2. The constructed model is implemented with Keras Python library.

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Downsampling the 512 or 256 Hz EEG recordings to 32 Hz

Segmentation into several parts with equal length

Calculating PSD of each segments with Hamming window length of 64 and 50 % overlap (PSD output has fixed length of 129 for every variation)

Splitting the data into 80% training set and 20% testing set.
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Figure 1. Schematic of preprocessing steps

```
1 x 129 x No. of channels

x1
x2
x3
...

1 x 90 x 50
1 x 45 x 50

Max-Pooling Scaling factor = 1/2

Flatten

Conv-Layer=ReLU Kernel size = 40

4 Classes

Fully Connected

1 x 2250

Figure 2. Architecture of 1D-CNN consisting of: 1 convolutional layer with 50 kernel filters whose size is 1x40 followed by Rectified Linear Unit (ReLU) activation, 1 pooling layer that outputs the maximum value of 2 adjacent elements, and 1 fully connected layer from 2250 flattened data to 4 classes of stroke identification.
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3. Result and Discussion
Some of the PSD obtained from EEG for each class can be seen in Figure 3. Second peak for each class has decreased in frequency as the severity of stroke increasing. It is in agreement with the theory that says Delta and Theta wave would become dominant when stroke occurred, while Beta and Alpha would experience some losses. For normal classes, second peak mostly occurs in frequency greater than 12 Hz, then slowly shifted to below 12 Hz for all classes of stroke. The bigger NIHSS score or the greater the level of stroke, this second peak frequency would shift more to the left.

We can see the total accuracy for each segment variation in Table 1. The accuracy of data changes as the segment length varies. We could see the accuracy getting better as more data are available for training. However, from 64 s and down the accuracy started decreasing due to the downsampling process of smaller segment that would distort the real signal. The best accuracy was achieved in 64 s segment.

![Figure 3. Examples of PSD obtained for Normal patients, Mild, Moderate and Severe Strokes](image)

| Segment Length (s) | #Training | #Testing | Accuracy (%) |
|--------------------|-----------|----------|--------------|
| 1024               | 48        | 12       | 58.3         |
| 512                | 136       | 34       | 79.4         |
| 256                | 316       | 79       | 89.9         |
| 128                | 644       | 161      | 93.8         |
| 64                 | 1316      | 329      | 97.3         |
| 32                 | 2305      | 577      | 96.8         |
| 16                 | 5300      | 1325     | 94.6         |

The performance of the classification model can be seen from the confusion matrix shown in Table 2-5 for some segmentation interval. Each class has different accuracy shown in Figure 4. Above 256 s segmentation, the available data for testing are very limited and the per-class-accuracy drop significantly, except for the mild class which is predicted correctly but the number of testing set is not enough to represent the performance.
Table 2. Confusion Matrix of 128 s Segment

|               | Predicted Class |
|---------------|-----------------|
|               | Normal | Mild | Moderate | Severe |
| Actual Class  | Normal  | 87   | 0        | 2       | 3       |
|               | Mild    | 2    | 22       | 0       | 0       |
|               | Moderate| 1    | 2        | 28      | 0       |
|               | Severe  | 0    | 0        | 0       | 14      |

Table 3. Confusion Matrix of 64 s Segment

|               | Predicted Class |
|---------------|-----------------|
|               | Normal | Mild | Moderate | Severe |
| Actual Class  | Normal  | 41   | 1        | 3       | 0       |
|               | Mild    | 0    | 7        | 2       | 0       |
|               | Moderate| 1    | 0        | 15      | 0       |
|               | Severe  | 0    | 1        | 0       | 8       |

Table 4. Confusion Matrix of 32 s Segment

|               | Predicted Class |
|---------------|-----------------|
|               | Normal | Mild | Moderate | Severe |
| Actual Class  | Normal  | 17   | 0        | 0       | 0       |
|               | Mild    | 0    | 2        | 3       | 0       |
|               | Moderate| 4    | 0        | 3       | 0       |
|               | Severe  | 0    | 0        | 0       | 5       |

Figure 4. Accuracy of Each Class: Normal, Mild, Moderate and Severe Stroke

The accuracy are calculated from architecture in Fig 2 which consists of 1 CL and 1 PL. For additional CL-PL in 128 s segment data, number of parameters and accuracy are changed. Second CL uses 20 filters with 1x20 kernel size, and the third uses 15 filters with 1x12 kernel size. The accuracies for using 1, 2 and 3 consecutively are 93.8%, 93.2% and 95.8%. Here we can see using only 1 CL still gives good accuracy where the trainable parameters are nearly half of using more CL. To reduce the trainable parameters, we need to decrease number of filters or increase the kernel size. Here we vary
number of filters into 5, 10, 20, 40, 50, 80 and the consecutive accuracies are 84.8%, 89.8%, 92.5%, 91.9%, 93.8%, 91.4%. It turns out that the maximum accuracy is reached when 50 filters are used. With the same filter number, we vary kernel size to 20, 40, 80 and 120 data, and the accuracies achieved are 90.1%, 92.6%, 93.6%, 93.4%, and 93.8%.

The execution time of training for each segment variation are 115.8 s, 59.6 s, 31.0 s, 14.3 s, 7.8 s, 4.4 s, and 2.8 s consecutively from the shortest to the longest segment. This time is nearly proportional to the number of input data.

4. Conclusion

From varying the length of segmentation in preparing the PSD calculation, number of CL, number of filter and kernel size the optimal accuracy achieved is when using 64 second segmentation, 1 CL, 50 filters and 1x120 kernel size. 97.3% accuracy is high enough considering the channels used in this study are only C3, C4, O1, and O2.

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