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Wavelet Decomposition and Feedforward Neural Network for Classification of Acute Ischemic Stroke based on Electroencephalography

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Abstract. Stroke is one of the leading causes of death in Indonesia. From 2013 to 2018, the prevalence of stroke increased from 7% to 10.9%. There are two types of strokes, namely Hemorrhagic and Acutte Ischemic Stroke (AIS) with the majority of it being AIS. Early detection and diagnosis are essential in stroke as it is a life-threatening disease, and the stroke treatment is based on its type. Currently, the gold imaging standards in stroke diagnosis are Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI). However, the mentioned services for stroke diagnosis are primarily available in hospitals classified as "class A" (general hospitals with extensive facilities and medical services). Compared to CT scans and MRI, electroencephalography (EEG) is a cost-friendly, non-invasive device studied for various brain-related diseases. This study aimed to determine the optimal epoch length to classify four stroke classes (healthy, minor, moderate, and severe) during resting condition for a machine learning-based AIS computer-aided diagnostics system. 32-channel EEG, CT scan, and NIHSS Scores were the obtained data. The features were delta-theta to alpha-beta ratio (DTABR), delta to alpha ratio (DAR), relative power ratio (RPR), and asymmetry, which were extracted using wavelet decomposition technique. The epoch length was varied by 1s, 2s, 10s, 30s, 60s, and 120s. The severity of stroke were classified using a feedforward neural network. The best performance was obtained at the 60-second epoch length with 89% accuracy using 15 hidden layers. This EEG-based diagnostic system would be expected to be implemented in "class C" hospitals, where only essential medical services and facilities are available, usually in rural areas.

Keywords: Acute Ischemic Stroke (AIS); Electroencephalography (EEG); Epoch length; Feedforward Neural Network (FNN); Wavelet decomposition

1. Introduction

Health Research conducted by the Indonesian Ministry of Health in 2013 and 2018 revealed an increase in stroke prevalence from 7% to 10.9% (Health Research and Development Department, 2018). This disease can be divided into two main types, ischemic and haemorrhagic. Acute Ischemic Stroke (AIS) constitutes the majority of stroke cases (85%), which happens when blood vessels to the brain are blocked or narrowed from fatty

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deposits (Rudd, 2016). The diagnosis of stroke is commonly facilitated by brain Computed Tomography (CT) scan or Magnetic Resonance Imaging (MRI). However, these neuroimaging devices are only available in "class A" hospitals, with extensive facilities and medical services. On the other hand, the hospitals in rural areas ("class C" hospitals) usually provide only the essential medical services with limited facilities and thus lack access to better and more expensive neuroimaging means. In addition, stroke rehabilitative services are only available in those large city hospitals (Kusuma et al., 2009). Meanwhile, based on a study in 2013, it was revealed that stroke was just as prevalent in rural areas as it was in the city (Health Research and Development Department, 2013). Therefore, an affordable alternative for stroke diagnostics, such as electroencephalography (EEG), is sorely needed in rural areas.

EEG is a non-invasive device that has been used in several research, such as for depression detection (Apsari & Wijaya, 2020), seizure detection (Srivastava et al., 2020), and stroke detection (van Putten, 2007). An EEG device is more affordable to procure than a CT scan or an MRI, and consequently less costly to operate. Ischemic stroke brain may present abnormalities in the EEG signal (Finnigan & van Putten, 2013). Typically, AIS EEG signals exhibit high delta activity (1-4 Hz). The delta power has been consistently identified as the marker for ischemic stroke. The alpha power, Brain Symmetry Index (BSI), delta-alpha ratio (DAR) and delta-theta alpha-beta ratio (DTABR) were also found to be good markers for stroke (Rahma et al., 2017; Finnigan et al., 2007; Müller et al., 2002). The delta band power and alpha to delta band ratio can distinguish patients who have sizeable ischemic stroke from other stroke patients (Shreve et al., 2019).

EEG comes with complex brain signals, and thus machine learning (ML) approach has been implemented as means to make sense of them. Extreme ML has been used to classify stroke features (Chan et al., 2019; Rahma et al., 2017), while XGBoost and principal component analysis were applied to improve classification accuracy in a small number of selected EEG channels (Fitriah et al., 2017). Convolutional Neural Networks, including Multi-Layered Perceptron, as well as Decision Tree and Artificial Neural Networks, have been used for EEG-based classification (Nurfirdausi et al., 2022; Dewi et al., 2020; Qureshi et al., 2018; Omar et al., 2014). One of the issues with classifying EEG signals using the ML approach is looking for the most optimal feature settings to obtain the best performance. Thus, this study explored variations of epoch lengths to investigate which length would yield the best results.

The current study is an extension of previous studies (Chan et al., 2019; Fitriah et al., 2017; Rahma et al., 2017) using the AIS dataset. The EEG data were obtained for healthy control and stroke patients as a 30-minute recording. NIHSS scores were referenced to separate patients into classes based on stroke severity, i.e., healthy, mild, moderate, and severe. EEG data were read and analyzed in MATLAB R2020A. The 30-minute recording was segmented into epochs of a certain length (120, 60, 30, 10, 2, and 1 second epochs) and features—such as relative power ratio (RPR), delta-theta alpha-beta ratio (DTABR), delta-alpha ratio (DAR), and asymmetry—were computed for each epoch. In the future, this program is expected to be implemented into the EEG hardware so that the most accurate prediction of stroke type can be obtained automatically in the shortest time possible. The features were classified into four classes based on stroke severity, and classification performance was obtained from that. Feedforward neural network was chosen as a classification algorithm because of its simplicity and advantage in handling nonlinear data.

2. Methods

2.1. Data Acquisition

Before the experiment, the patients were given informed consent regarding their availability and willingness as subjects. The subjects comprised 29 healthy controls, 9 mild stroke patients, 23 moderate stroke patients, and 5 severe stroke patients. Healthy controls did not have any stroke onset before the data acquisition, while stroke patients were those who had an ischemic stroke within 72 hours or less after start. This study included 39 male and 27 female patients aged 40 to 74 years old. Table 1 contains demographic information for each subject.

Table 1 Participant's demographic and characteristics based on stroke severity

Subject Number	Patient	Stroke Severity	Age	Gender	Onset time	NIHSS	EEG Device	Frequency Sampling
1	stroke	moderate	43	M	20	4/4	Xltek	512
2	stroke	moderate	48	F	24	10/5	Biologic	256
3	stroke	moderate	43	M	48	12/7	Biologic	256
4	stroke	mild	60	F	6	1/1	Biologic	256
5	stroke	mild	56	F	6	2/1	Biologic	256
...	...	...	...	...	...	...	...	...
66	stroke	mild		F			Xltek	512

The EEG devices used in this study were the Biologic Netlink System and the Xltek EEG 32U Natus, both had 32 channels and 512 Hz sampling frequency. The electrode placement was based on the international 10–20 system and was saved in European Data Format (.edf). Each AIS patient's EEG recording was accompanied by their NIHSS score, CT scan, and EEG interpretation from the supervising physician. NIHSS score defines the level of stroke severity: 0 indicates no stroke, 1–4 indicates minor stroke, 5–15 indicates moderate stroke and above 15 indicates severe stroke (Rahma et al., 2017).

2.2. Signal Processing and Features

After data collection, pre-processing using Independent Component Analysis (ICA) was done automatically in the device. The signals were then decomposed into their respective frequency bands using wavelet transformation, and their features were calculated before inputting into the ML algorithm. The features calculated in this study were relative power ratio (RPR), delta-alpha ratio (DAR), delta-theta alpha-beta ratio (DTABR), and asymmetry.

2.2.1. Segmenting into Multiple Epochs

The standard procedures for EEG recording were based on the conditions shown in Table 2. The total recording time was 30 minutes, which were divided as follows:

Table 2 EEG data timepoints and their recording conditions

Minute	Description
0-3	eyes closed
3-6	eyes open
6-9	photic stimulation
9-12	hyperventilation (rapid inhale and exhale)
12-30	eyes closed; patients were asked to sleep if they could

In this study, only eyes closed conditions were used. The reason for this was to investigate AIS markers during resting condition. The total eyes closed recording was 18 minutes. This recording was then divided into multiple epochs of various lengths, which are

120, 60, 30, 10, 2, and 1 second epochs. Each epoch was transformed to a frequency domain using wavelet transformation.

2.2.2. Wavelet Transformation

Wavelet transformation is a time-to-frequency domain transformation that utilizes wavelets called the "mother" and "daughter" wavelets. Wavelet is concentrated in both time and frequency, whereas standard Fourier transforms is localized only in frequency (Agarwal et al., 2017). It is known to localize signal components better than other methods (Sanei & Chambers, 2007). The wavelet is represented as:

$$\gamma_{\kappa}(\omega_{\alpha}, t) = \int_{-\infty}^{\infty} x(t+\tau)\psi^{*}_{\omega_{\alpha},\kappa}(\tau)d\tau \tag{1}$$

where ω_{α} is the angular frequency, κ is the wavenumber, and $\psi_{\omega\alpha,\ \kappa}(\tau)$ is the wavelet function.

Wavelet transformation can be classified into two types: Continuous Wavelet Transformation (CWT) and Discrete Wavelet Transformation (DWT). For this study, DWT was used to decompose the EEG signals into their respective frequency bands: delta, theta, beta, alpha, and gamma. DWT discreetly samples the signal and acts like a filter bank that takes the input signal and outputs the coefficients of the signal. Decomposing EEG signals into their respective frequency components can be done using a multi-level DWT decomposition (Tumari et al., 2013).

To decompose a signal of EEG, the window function and the level of decomposition must be appropriate for the signal. The frequency sampling of the acquisition was 512 Hz, which means that the recorded signal is 0-512 Hz. A 7-level decomposition was required to decompose these signals. The window function used in this study was Daubechies 4 (db4) due to its small mean square error (MSE) when used for EEG signals (Tumari et al., 2013).

The decomposed signals consisted of approximation (A) and detail (D) signals. The first three decompositions (D1, D2, and D3) were not used because they were considered as noise (Tumari et al., 2013). EEG frequency bands were obtained from the decomposition of AD3, which were D4 (gamma band, 32 – 64 Hz), D5 (beta band, 16 – 32 Hz), D6 (alpha band, 8 – 1 6 Hz), D7 (theta band, 4 – 8 Hz), and AD7 (delta band, 0 – 4 Hz).

2.2.3. Relative Power Ratio

Relative power ratio is the ratio between a certain frequency band's power and all bands' total power. The RPR of a certain frequency band is computed using the equation:

$$\mathrm{RPR}(f_1, f_2) = \frac{P(f_1,f_2)}{P(f_L,f_H)} \times 100\% \tag{2}$$

where f_1 and f_2 are the low and high boundaries of the frequency band, f_L and f_H are the low and high boundaries of all bands. $P(f_1, f_2)$ refers to the band power of a particular frequency band, while $P(f_L, f_H)$ refers to the total power of all bands.

2.2.4. Delta-Alpha Ratio (DAR)

Delta-alpha ratio (DAR) is the ratio between the delta band's power and the alpha band's power. DAR is calculated using the equation:

$$\mathrm{DAR} = \frac{\mathrm{RPR_{delta}}}{\mathrm{RPR_{alpha}}} \tag{3}$$

DAR in AIS patients' EEG signals was found to be higher than healthy controls, with higher variability as well (Finnigan et al., 2016).

2.2.5. Delta-Theta Alpha-Beta Ratio (DTABR)

Delta-theta alpha-beta ratio (DTABR) is the ratio between the slow (delta and theta) and fast (alpha and beta) EEG waves. DTABR is calculated using the equation. DTABR in AIS patients was found to be relatively higher than in healthy controls (Finnigan et al., 2016).

$$\text{DTABR} = \frac{\text{RPR}_{\text{delta}}+\text{RPR}_{\text{theta}}}{\text{RPR}_{\text{alpha}}+\text{RPR}_{\text{beta}}} \tag{4}$$

2.2.6. Asymmetry

Asymmetry is the measure of activity between the left and right brain, calculated using the band power of each EEG frequency band. A high asymmetry indicates that the brain in that frequency band is more dominant in the left or right hemispheres. When asymmetry is positive, it indicates that the right hemisphere is more dominant. When it is negative, then the left hemisphere is more dominant (Allen et al., 2004). The calculation of asymmetry is as follows:

$$asymmetry = \frac{1}{N}\left(\sum_{n=1}^{N} \ln P_{x\,right} - \sum_{n=1}^{N} \ln P_{x\,\text{left}}\right) \tag{5}$$

where N is the number of electrodes on each hemisphere and P_x is the band power of frequency band x for each electrode.

This study calculated nine asymmetry features from eight left-right electrode pairs and the total left-right hemispheric asymmetry. These features can be further explained as follows: prefrontal (FP2 – FP1); frontal 1 (F4 – F3); frontal 2 (F8 – F7); temporal 1 (T2 – T1); temporal 2 (T4 – T3); central (C4 – C3); parietal (P4 – P3); occipital (O2 – O1).

2.3. Machine Learning Classification

2.3.1. Feedforward Neural Network

Feedforward neural network or multilayer perceptron (MLPs) is the first artificial neural network that does not have a loop for their connections. In this network, information only flows forward from the input nodes to the hidden layers (if any) and the output node, hence the name "feedforward". It is also divided into two groups depending on the number of the layers, which are single-layer and multi-layer (SAZLI, 2006). Feedforward neural network is considered simple compared to a recurrent neural network (RNN), in which is constructed as a loop. This chain's length is called the network's depth.

2.3.2. K-Fold Cross Validation

Cross-validation is a sampling method to estimate the performance of a predictive model in testing with the advantage of giving insight into performance from an independent dataset. It separates the dataset into portions and utilizes different parts of that data as either testing or training data in each of its iterations. The estimation of cross-validation accuracy is the number of correct classifications divided by the total data in the dataset. In k-fold cross-validation, the dataset will be randomly divided into equal sizes of subsets or folds.

$$Acc_{CV} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{1 - h_1}\right)^2 \tag{6}$$

The results of k-fold cross-validation are averaged from the results of k number of subsets. In k-fold cross-validation, all subsets will take turns as training and validation data, but each subset will only be used once for validation. The standard parameter -k on k-fold cross-validation is 10, however, it remains an undetermined parameter (Seni & Elder, 2010).

3. Results and Discussion

3.1. Features Analysis

Features capable of identifying healthy and stroke patients were calculated to differentiate between the two main classes. Based on four groups classification, DAR and DTABR showed an incremental increase in moderate and severe stroke compared to control, as shown in Figure 1. Higher DAR and DTABR in stroke patients are caused by the slowing in brain activity, thus lower wave signals become more significant compared to healthy controls (Finnigan et al., 2016). However, a small increase was seen for mild stroke compared to healthy controls.

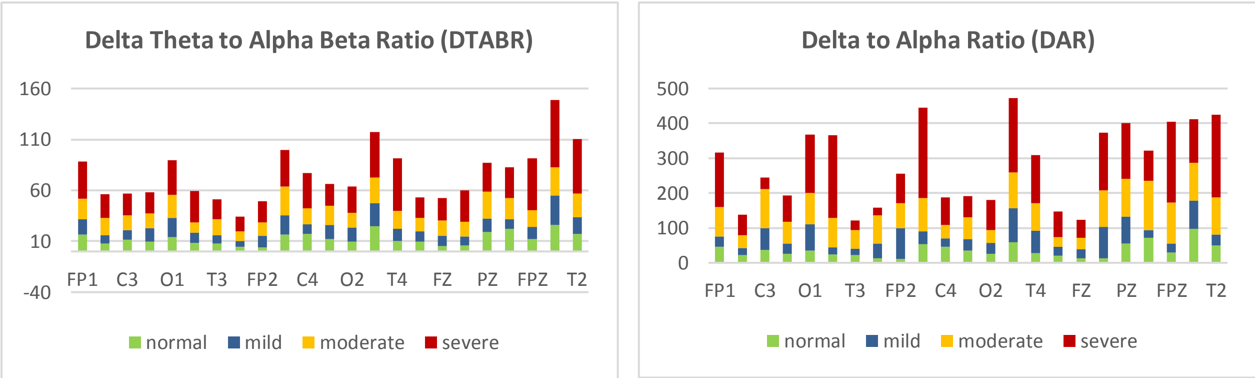

Figure 1 Comparison of DAR and DTABR among stroke severity level: normal, mild, moderate, and severe

In addition to DAR and DTABR, RPR was calculated using Decomposition Wavelet Transform (DWT). Figure 2 shows RPR in different frequency bands of EEG: alpha RPR, beta RPR, delta RPR, and theta RPR based on the level of stroke severity. The slight dominance of delta RPR is shown in mild stroke patients compared to normal subjects. In moderate and severe stroke patients, delta dominated the brain signals. Severe stroke patients had an abnormally dominant delta band, especially in the prefrontal areas (FP1, FP2, and FPZ), which proves that stroke patients have unusually high power of slow waves in their brains. Figure 2 shows that the alpha RPR of moderate stroke is slightly lower compared to the alpha RPR of mild stroke.

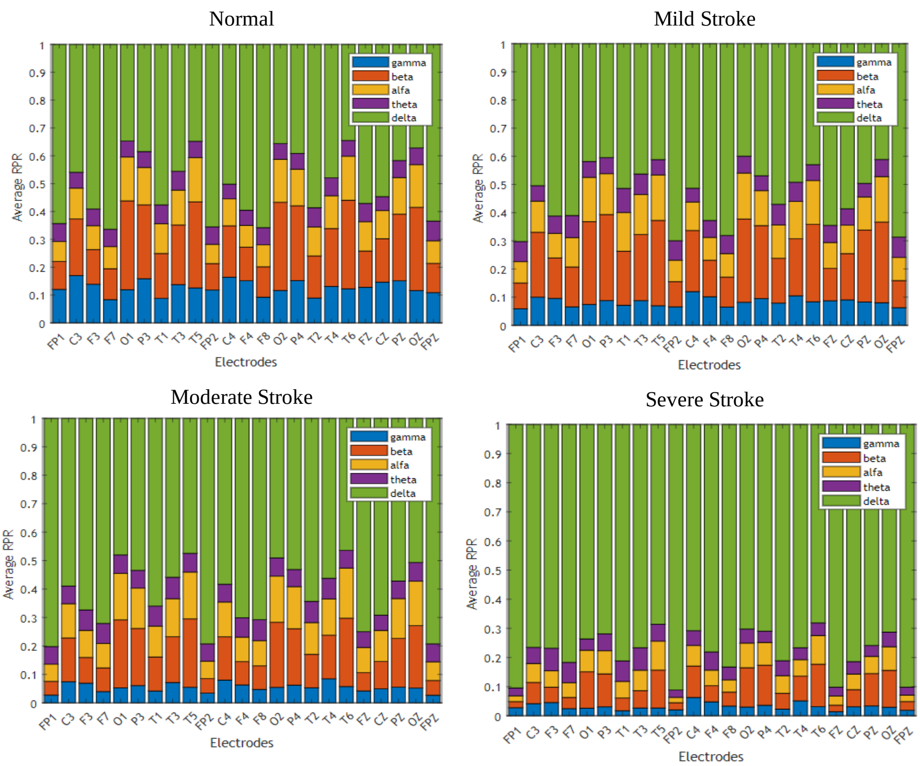

Figure 2 Relative Power Ratio (RPR) comparison among all stroke severity level

The last feature observed in this study was the asymmetry of each channel pair, shown in Figure 3. Out of all channel pairs, the central pair showed the most significant asymmetry difference between healthy controls and stroke patients, with values of 0.36 and -2.75, respectively. This indicates that stroke patients generally have more left hemisphere activity in the central region. In general, healthy controls have a relatively small asymmetry between hemispheres, with a slight tendency on either right or left side dominance. Besides the central pair, only narrow differences between control and stroke were found between hemispheres.

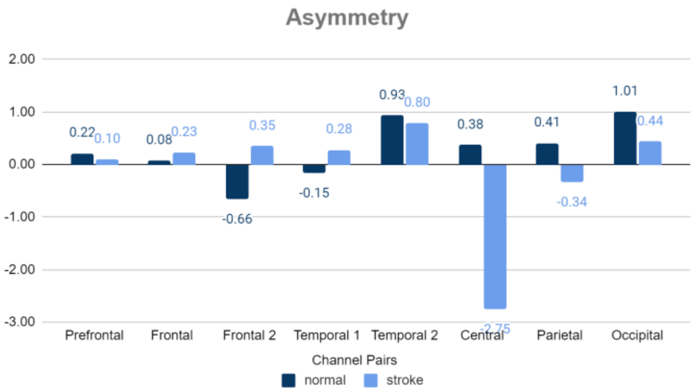

Figure 3 Asymmetry scores between healthy and stroke patients

3.2. Training and Classification Result

A feedforward neural network is implemented to classify AIS severity levels into four categories: normal or healthy controls, mild, moderate, and severe. The ML training was conducted using MATLAB R2020A with Intel® Core™ i7-8809G CPU@ 3.10GHz and 32 GB RAM. Each epoch length variation was trained and tested using the chosen ML algorithm to determine which would yield the best performance based on accuracy, specificity, and sensitivity. Besides epoch length, hidden layers were also varied to find the number of hidden layers required to achieve the best performance. RPR, DAR, DTABR, and asymmetry features were included as input in the ML classification without any exclusions.

Table 3. shows the training result of the dataset. In general, ML performance increased with the number of hidden layers used—peaking at 15 hidden layers—but performance decreased at 20 hidden layers. The same was observed for epoch length, which achieved the best performance at a 60-second length and decreased at a 120-second length.

Table 3 Performance results

Parameter		120 seconds			60 seconds			30 seconds		
		Acc	Spec	Sen	Acc	Spec	Sen	Acc	Spec	Sen
Hidden layer	5	75%	75%	90%	63%	51%	96%	65%	48%	97%
	10	72%	73%	87%	80%	86%	100%	67%	68%	100%
	15	66%	66%	93%	**89%**	**100%**	**88%**	83%	100%	100%
	20	65%	65%	86%	71%	58%	97%	76%	54%	99%

Parameter		10 seconds			2 seconds			1 second		
		Acc	Spec	Sen	Acc	Spec	Sen	Acc	Spec	Sen
Hidden layer	5	57%	45%	100%	68%	68%	96%	62%	61%	97%
	10	70%	61%	100%	60%	70%	100%	62%	62%	100%
	15	72%	69%	100%	80%	80%	88%	63%	64%	100%
	20	74%	70%	100%	80%	80%	97%	68%	68%	99%

The best configuration was acquired at a 60-second epoch length with 15 hidden layers, which performed 89% accuracy, 88% sensitivity, and 100% specificity. The 60-second epoch gave the most optimum result among others. The shortest epoch length, a 1-second epoch, produced the worst results overall.

The lowest accuracy was obtained using 10 hidden layers, 60% for the 2-second epoch, compared to the accuracy obtained by 60 seconds, 80%. This occurred because longer segments contained more signal information than shorter segments, which resulted in better feature calculations.

4. Conclusions

This study calculated features that could identify stroke from healthy controls from resting EEG signals, which were delta theta to alpha beta ratio (DTABR), delta to alpha ratio (DAR), relative power ratio (RPR), and asymmetry. Stroke patients had higher delta RPR value as compared to healthy controls. Differences between control and stroke patients were identified. Stroke patients had higher delta RPR value as compared to healthy controls. In general, as stroke severity increases, so does the dominance of the delta band. Severe stroke showed a very dominant delta compared to the other bands, especially in the prefrontal region. Feedforward neural network and AIS EEG features were utilized to identify stroke and predict its severity from resting EEG data. The EEG signals were segmented into different epoch lengths, and the neural network's hidden layers varied. For this study, the optimum network configuration was 60-second epochs with 15 hidden layers. This simple configuration could classify stroke into four different classes with the best accuracy of 89%, specificity of 100%, and sensitivity of 88%. Further studies could implement feature-selection methods such as Principal Component Analysis (PCA) to reduce dimensionality and improve classifier performance. The result of this study shows a promising future for a more robust AIS computer-aided diagnostic system that uses EEG as an alternative neuroimaging device for stroke diagnosis.

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