Obstructive sleep apnea detection based on electrocardiogram signal using one-dimensional convolutional neural network

Rahmat Widadi[1], Achmad Rizal[2], Sugondo Hadiyoso[3], Hilman Fauzi[2], Ziani Said[4]
[1]Department of Biomedical Engineering, Faculty of Telecommunication and Electrical Engineering, Institut Teknologi Telkom Purwokerto, Purwokerto, Indonesia
[2]School of Electrical Engineering, Telkom University, Bandung, Indonesia
[3]School of Applied Science, Telkom University, Bandung, Indonesia
[4]Department of Health Technologies Engineering, Research Group in Biomedical Engineering and Pharmaceutical Sciences, ENSAM, Mohammed V University, Rabat, Morocco

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ABSTRACT

Obstructive sleep apnea (OSA) is a respiratory obstruction that occurs during sleep and is often known as snoring. OSA is often ignored even though it can cause cardiovascular problems. Early diagnosis is needed for prevention towards worse complications. OSA clinical diagnosis can use polysomnography (PSG) while the patient is sleeping. The PSG examination includes calculating total apnea plus hypopnea every hour during sleep. However, PSG examination tends to be high cost, takes a long time, and is impractical. Since OSA is related to breathing and heart activity, the electrocardiogram (ECG) examination is an alternative tool in OSA analysis. Therefore, this study proposes OSA detection on single lead ECG using one-dimensional (1D)-convolutional neural network (CNN). The proposed CNN architecture consists of 4 convolutional layers, 4 pooling layers, 1 dropout layer, 1 flatten layers, 2 dropout layers, 1 dense layer with rectified linear unit (ReLU) activation function, and 1 dense layer with SoftMax activation function. The proposed method was then tested on the ECG sleep apnea dataset from PhysioNet. The proposed model produces an accuracy of 92.69% with the average pooling scenario. The proposed method is expected to help clinicians in diagnosing OSA based on ECG signals.

Corresponding Author:

Sugondo Hadiyoso
School of Applied Science, Telkom University
Bandung, Indonesia
Email: sugondo@telkomuniversity.ac.id

1. INTRODUCTION

One of sleep disease or sleep disorder in obstructive sleep apnea (OSA) [1]. OSA conditions occur if the intake of air is stopped for 10 seconds or more during sleep inspiration [1]. Apnea causes obstruction because the body's muscles relax, causing the airways to collapse [2]. If the airway is closed, the patient will wake up during sleep or experience a sudden transition to sleep. OSA is associated with several diseases, including hypertension and several cardiovascular diseases such as heart failure or myocardial ischemia [3].

Depending on the signal to be observed, several methods are used to diagnose OSA. Became one of the OSA observation standard is polysomnography (PSG). The disadvantage of this PSG is that it is time-consuming, costly, and impractical, so it is only performed on patients with a specific level of severity [4]. Through patient movement, video processing can be used to detect OSA [5]. Speech processing methods can be used to analyze snoring so that OSA can be detected [6]. The analysis of speech signals is frequently used to analyze sleep apnea using respiratory signals [7]. Voice activity detection (VAD) is a popular algorithm for detecting the presence or absence of the respiratory process during sleep [8].

Numerous studies have examined the relationship between electrocardiogram (ECG) signals and respiration, called as electrocardiogram-derived respiration (EDR) [9]. Respiration influences ECG signals through a variety of mechanisms, including changes in thorax impedance resulting from lung volume changes [10]. The subsequent mechanism is the alteration of the heart vector due to shifts or changes in heart orientation associated with ECG electrodes [11], [12].

OSA classification using single-lead ECG has been explored by many researchers using various methods. There are two essential parts in the OSA ECG classification process: feature extraction and classification. In the feature extraction process, the heart rate variability (HRV) parameter is one of the top choices for many researchers because it can be directly extracted from the ECG signal. Median, mean, skewness (third momentum), kurtosis, minimum, and range calculated to get the HRV parameters. Another parameter derived from the internal R-R is the standard deviation of successive differences between adjacent R–R intervals (SDSD).

Differences in the number of R-R intervals that exceed a specific time, such as 50 ms or 20 ms, are also extracted parameters such as NN50, NN20, pNN50, and pNN20 [13]. The extracted features can also be features from the frequency domain. This frequency component usually represents the activities of thermoregulation mechanisms, sympathetic activity, and parasympathetic activities [11]. Characteristics associated with this frequency include the very low-frequency (VLF) band, low-frequency (LF) band, and high-frequency (HF) band. Another method used for feature extraction is signal decomposition, and then feature extraction is performed. For example, Zarei and Asl [14] used wavelet transforms and entropy for ECG OSA classification. Another study used multiscale entropy as a feature [15]. This method is based on multiscale signal complexity, which is considered related to OSA ECG.

The following process in the OSA ECG classification is the classifier. The support vector machine (SVM) is one of the most widely used machine learning classifiers [16]. In its development, deep learning is the next choice because of its advantages in performing feature extraction automatically [17]. Even so, some researchers still combine feature extraction and deep learning. Singh and Majumder [18] used a scalogram and convolutional neural network (CNN) to produce an accuracy of 86.2%. Bahrami and Forouzanfar [19] used long short-term memory (LSTM) to have 80.67% accuracy, 75.04% sensitivity, and 84.13% specificity. Meanwhile, another group of researchers using LTSM produced the highest accuracy of 99.8% with RR interval as a feature [20]. The RR interval combined with a multiscale dilation attention (MSDA)-one dimensional convolutional neural network (1D-CNN) resulted in the highest accuracy of 89.4% [21]. From the several studies that have been described, it can be divided into two groups; those who use the feature extraction method and who do not use the feature extraction method. Apart from these differences, another difference is the method of processing or cutting data from the dataset used. To compare the performance of deep learning for OSA classification from a single lead ECG without a feature extraction process, it is necessary to try using deep learning directly without a feature extraction process or trimming the ECG signal further.

In this study, the classification of normal and OSA ECG signals was carried out using 1D-CNN. Long-time ECG recording was cut into minute segments and used to input the 1D-CNN. In this study, the feature extraction process was not carried out but directly using the clipped ECG signal. CNN is optimized to get the best configuration to produce the highest accuracy. The proposed method can be an alternative for ECG signal processing, especially for OSA signal classification.

2. MATERIAL AND METHODS

In this research, a modified CNN is proposed to solve the OSA ECG signal classification problem. Figure 1 shows the block diagram of the proposed 1D-CNN. The proposed 1D-CNN architecture to classify OSA ECG signals consists of 4 convolutional layers, 4 pooling layers, 1 dropout layer, 1 flatten layers, 2 dropout layers, 1 dense layer with rectified linear unit (ReLU) activation function, and 1 dense layer with SoftMax activation function.

2.1. Dataset

This study used the PhysioNet ECG sleep apnea dataset [22], [23]. There are 70 records, with 35 belonging to the training set and 35 to the testing set. Each recording consists of a digital ECG signal and is annotated by an expert [24]. ECG signal recording length ranges from seven to ten hours. In some recordings there are also additional signals such as respiration and oxygen saturation, but these additional signals were not used in this study. The ECG signal is truncated every 6,000 samples. This number is equal to a one-minute signal because it has a sampling frequency of 100 Hz. This process produces 17,010 data for train and test the proposed method. The normal ECG and OSA signals are shown in Figure 2. Based on Figure 2, the OSA ECG signal Figure 2(a) has a different orientation in the spike area compared to normal ECG signals in Figure 2(b).

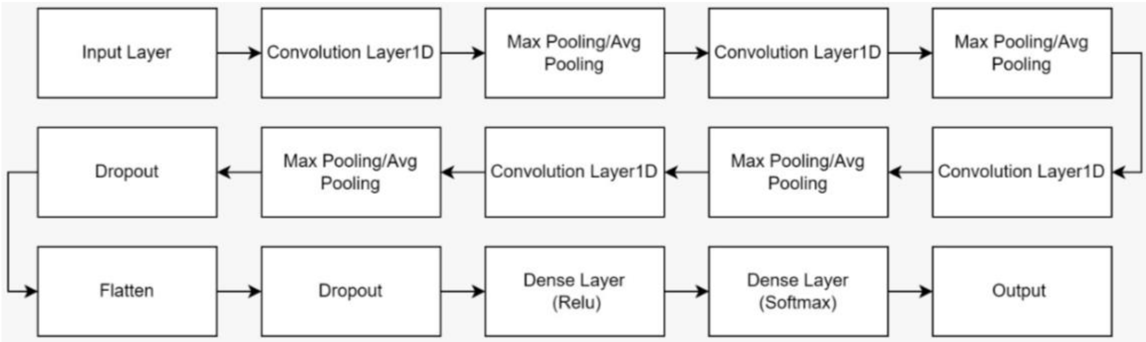
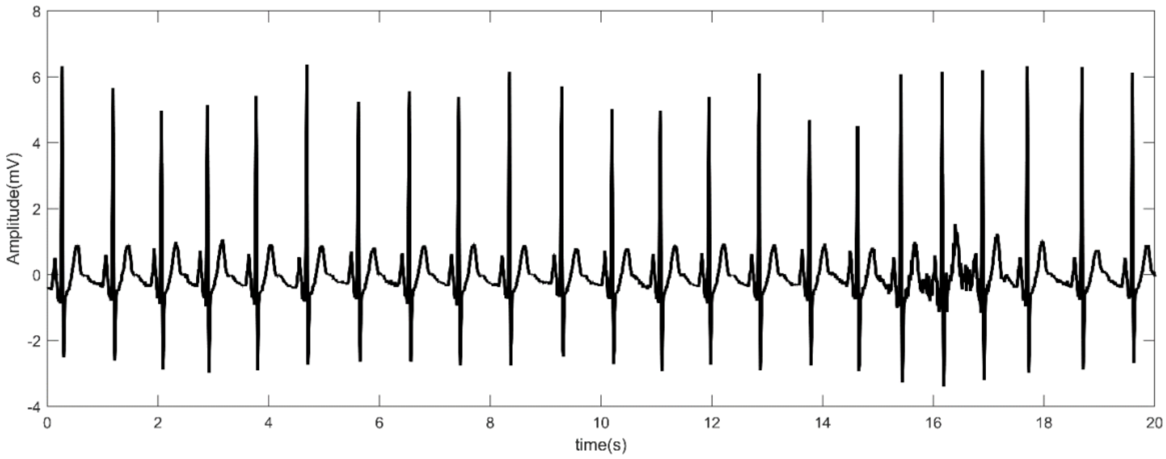
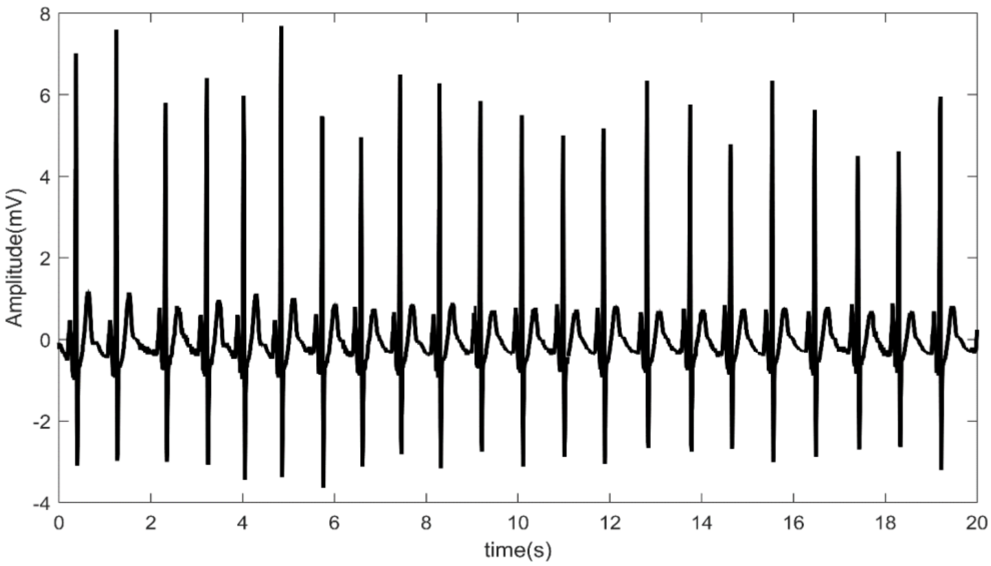


Figure 1. Block diagram of proposed 1D-CNN



(a)



(b)

Figure 2. Normal and OSA ECG signal, (a) standard ECG, one minute recoding and (b) OSA event in ECG of the same subject

2.2. One-dimensional convolutional neural network

In general, 1D-CNN consists of two parts, namely the convolution layer and the multilayer perceptron (MLP) layer [25]. In this study, the input of 1D-CNN is a multichannel ECG signal, and the output is the class of the input signal. Figure 3 shows the general structure of a 1D-CNN. The convolution layers have convolution, pooling, and flattening processes [26]. In the convolution process, there are kernels that are shifted and multiplied by input signals. If the input signal $x(n)$ is of length n and the kernel is $h(k)$ of length k. Each kernel is shifted by$s$ (stride) after multiplied by $x(n)$. The convolution process between $x(n)$ and $h(k)$ is defined in (1).

$$y(n) = \begin{cases} \sum_{i=0}^{k} x(n-i)h(i) \ , n = k-1 \\ \sum_{i=0}^{k} x(n-i+ s-1)h(i) \ , otherwise \end{cases} \tag{1}$$

Figure 3. 1D-CNN structure

The output of the convolution process is used in the pooling process to reduce the signal size [27]. Two types of pooling used in this study are average pooling and max pooling. Average pooling takes the average value of the signal window along f. This window or filter is shifted on the signal by a shift of s (stride). A similar process occurs in max pooling, only that the value taken is the maximum value instead of the average. Figure 4 shows example of max pooling process.

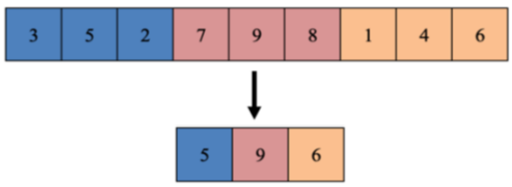


Figure 4. Example of max pooling operation: window size =3, stride =3

The next operation on convolution layers is flatten. The output signal in pooling operation has dimensions of more than 1. To be used as input for the MLP stage, it needs to be converted into 1 dimension. Figure 5 is an illustration of the flatten process.

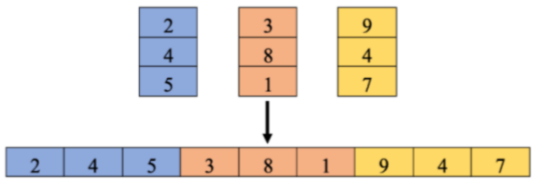


Figure 5. Flatten process

The signals that have been flattened can be used as MLP inputs. MLP is also known as a fully connected layer. This term is because each neuron in the previous layer is connected to all neurons in the next layer. Figure 6 shows an example of an MLP with an input layer, one hidden layer, and an output layer. There are seven neurons, namely x_1 and x_2 on the input layer, h_1, h_2, h_3 on the hidden layer, $o_1$and o_2 on the input layer. The output of neurons in the hidden layer is determined using (2).

$$y = f(w^T x) \tag{2}$$

Inner product weight w with input x is given to the activation function f so that it is non-linear. The activation function used in this study is ReLU. The ReLU function is defined (3) [28].

$$y = \max(0, w^T x) \tag{3}$$

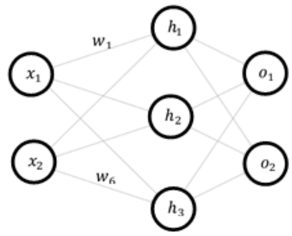


Figure 6. Example of MLP [29]

3. RESULTS AND DISCUSSION

The OSA detection system is tested for system performance by calculating system accuracy based on two types of pooling: max pooling and average pooling. This accuracy measurement is carried out to determine the difference in the effect of the type of pooling with the length and number of filters on system accuracy. Filters vary from 1-10 while the number of filters is set to 5, 10, 15, and 20 filters. In addition to accuracy, system performance measurements were also carried out with training parameters and validation loss for each type of pooling. The distribution of OSA data is 80% for training and 20% for testing.

3.1. Max pooling test

The first stage is the training process, 1D-CNN is trained using 13,608 OSA data. System performance is measured based on the loss parameter in the system training and validation process. One example of the training process that will be discussed in this section is 1D-CNN with max pooling, filter length is 7, and the number of filters is 15. Based on the loss measurement results, the gap between the validation process and system training process loss values are getting higher as the epoch increases. The value of the gap loss at the 50th epoch is 0.05, with the training loss and validation loss values are 0.16 and 0.21, respectively. However, the trend of loss values from the two processes has decreased with a similar pattern, as shown in the graph in Figure 7.

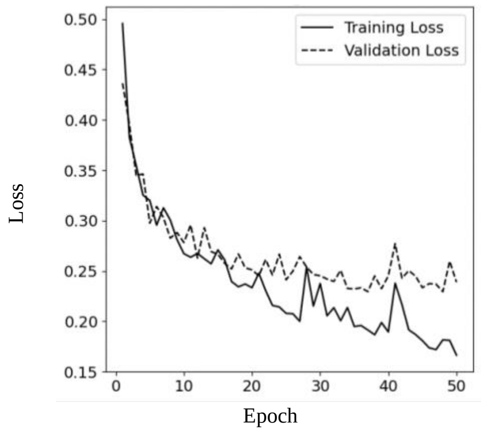


Figure 7. Training and validation loss on 1D-CNN by using filter length 7, number of filters 15, and max pooling

The performance calculation of the system model classification is performed using the confusion matrix from the testing stage. 1D-CNN was evaluated using 3,402 OSA data. The system model is a system with max pooling at a filter length of 7, the number of filters is 15, and the epoch is 50th. The confusion matrix value is obtained based on the evaluation results, as shown in Figure 8.

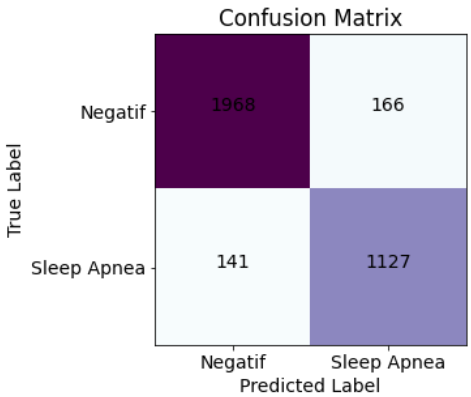


Figure 8. Example of a confusion matrix of max pooling 1D-CNN

Furthermore, by using an accuracy calculation based on the value of the confusion matrix, a system classification accuracy of 90.8% is obtained.

$$Accurracy = \frac{1,127+1,968}{1,127+1,968+166+141}\ x\ 100\% = 90.8\%$$

The results of measuring system accuracy using max pooling get considered good results. The accuracy system results with max pooling can be seen in Table 1. The highest average accuracy of the system based on filter length is 90% at a filter length of 9. Furthermore, the highest average accuracy system based on the number of filters occurs in the number of filters 20, with an accuracy of 88.50%. Specifically, based on the filter length and the number of filters on the max pooling type, the highest system accuracy was performed at 91% on filter lengths of 7 and 10 with the filter numbers of 15 and 20.

Table 1. Accuracy of 1D-CNN with max pooling

Pooling type	Filter length	Accuracy (%)				Average
		5 Filters	10 Filters	15 Filters	20 Filters	
Max Pooling	1	65.00	83.00	69.00	81.00	74.50
	2	79.00	86.00	83.00	87.00	83.75
	3	81.00	88.00	89.00	88.00	86.50
	4	85.00	89.00	88.00	90.00	88.00
	5	85.00	88.00	90.00	90.00	88.25
	6	89.00	90.00	90.00	90.00	89.75
	7	88.00	90.00	91.00	91.00	90.00
	8	87.00	90.00	90.00	90.00	89.25
	9	89.00	90.00	90.00	89.00	89.50
	10	87.00	89.00	91.00	89.00	89.00
	Average	83.50	88.30	87.10	88.50	

3.2. Average pooling test

In measuring the loss ratio of the training and validation system process, it was found that the measured loss pattern decreased as the epoch value increased. In addition, compared to systems with the max pooling type, systems with average pooling that use a filter length of 9 and number of filters of 20 have a lower average gap loss between the training and validation processes. The graph of the ratio of the value of training loss and validation loss based on the size of the epoch can be seen in Figure 9.

The system accuracy results with average pooling can be seen in Table 2. Based on the results of testing the system on the average pooling type, the highest average accuracy value based on filter length is obtained on all criteria for the number of filters, with a value of 91.51% at a filter length of 9. Meanwhile, the highest average accuracy value based on the number of filters occurs in the number of 10 filters, with a value of 87.42%. In testing the system with a specific filter length and number of filters, an accuracy of 92.69% is obtained with a filter length of 9 with a number of 20 filters. With the accuracy value obtained, the system is considered to have good performance in detecting OSA by processing the ECG signal using an average pooling.

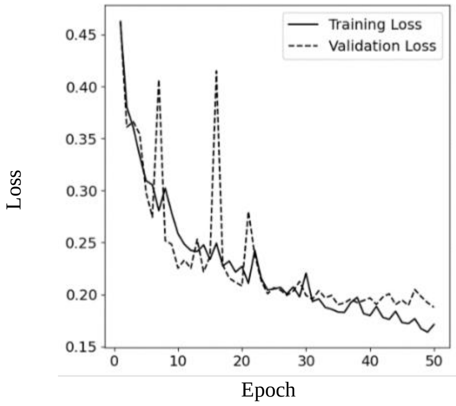


Figure 1. Training and validation loss on 1D-CNN by using filter length 9, number of filters 20, and average pooling

Table 2. Accuracy of 1D-CNN with average pooling

Pooling Type	Filter Length	Accuracy (%)				Average
		5 Filters	10 Filters	15 Filters	20 Filters	
Average Pooling	1	60.12	69.43	74.15	64.71	67.10
	2	82.99	85.09	76.27	66.49	77.71
	3	85.32	88.22	84.34	90.05	86.98
	4	85.11	87.18	88.87	89.36	87.63
	5	86.24	89.95	91.34	91.89	89.86
	6	88.05	91.02	88.97	91.44	89.87
	7	89.61	91.36	92.00	91.63	91.15
	8	86.93	90.06	92.20	91.79	90.25
	9	89.52	91.55	92.26	92.69	91.51
	10	90.57	90.30	90.91	90.95	90.68
	Average	84.45	87.42	87.13	86.10	

3.3. Performance comparison with previous studies

Table 3 presents previous studies related to OSA detection based on ECG signal. The comparison here only uses research from the same data. This is intended to make the comparison fairer. Based on Table 3, the method proposed in this paper has higher accuracy than previous studies.

Table 3. Comparison with previous studies

Ref.	Feature extraction	Classifier	Accuracy (%)
[15]	Multiscale entropy	SVM	85.6
[3]	Heart rate variability	SVM	89.5
[30]	Discrete wavelet transforms, 1st order statistics	Bagged trees	89.2
Proposed method	N. A	1D-CNN	92.69

The advantage of this method is that it does not require a separate feature extraction process. CNN has the ability to perform feature extraction automatically. The configuration of the designed CNN determines accuracy. The weakness of using CNN is that it requires a large enough dataset for sufficient training. In addition, it requires repeated optimization to get the configuration that produces the highest accuracy. Experiments using other deep learning methods are an interesting research topic at a later stage.

4. CONCLUSION

Based on the results of measuring system performance with two types of pooling: max pooling and average pooling, it is found that the average pooling type can produce better performance. It is evidenced by measuring accuracy based on the filter effect, loss based on epoch values, and classification accuracy based on confusion matrix values, all of which show that a system with average pooling is better than max pooling. Based on the value of accuracy and the ability of the system to classify data, average pooling is considered capable of providing higher values of 1.69% and 2.1%, respectively. In addition, even though both systems show a similar loss pattern trend that both decrease in direct proportion to increasing epochs, the gap between the training and validation loss values in the system with average pooling shows less value than the system with max pooling. It shows that a system with average pooling using a filter length of nine with several 20 filters at the 50th epoch is proven to detect OSA through ECG signal processing with excellent system accuracy and stability.

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BIOGRAPHIES OF AUTHORS

Rahmat Widadi obtained a master's degree in engineering at the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada in 2018. Since that year he has also been a lecturer at Institut Teknologi Telkom Purwokerto. His homebase is in biomedical engineering with research interests related to signal processing either one-dimensional or two-dimensional signals and artificial intelligence. Currently he is pursuing his doctoral studies at the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada. He can be contacted at email: rahmat@ittelkom-pwt.ac.id.

Achmad Rizal received Bachelor of Engineering in Telecommunication Engineering from STT Telkom (now, Telkom University), Bandung Indonesia in 2000. He received master's degree in biomedical engineering from Institut Teknologi Bandung, Bandung, Indonesia in October 2006. Received Ph.D. degree from Universitas Gadjah Mada, Yogyakarta, Indonesia. His research interests include biomedical signal processing, biomedical image processing, biomedical instrumentation, and telemedicine. Now he is associate professor in School of Electrical Engineering, Telkom University. He can be contacted at email: achmadrizal@telkomuniversity.ac.id.

Sugondo Hadiyoso received the Doctor in Electrical Engineering from Institut Teknologi Bandung, Indonesia in March 2023. Since 2010, he joined as a Lecturer in the Diploma of Telecommunication Technology, School of Applied Science, Telkom University. He is also currently members of Biomedical Instrumentation Research Group in Telkom Univesity. His research interests are wireless sensor network, embedded system, logic design on FPGA, and biomedical engineering. The focus of his doctoral research is signal processing and analysis of EEG signals. He can be contacted at email: sugondo@telkomuniversity.ac.id.

Hilman Fauzi received his master's degree from STEI Institut Teknologi Bandung, Indonesia in 2013. He received Ph.D. from Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia (UTM), Malaysia in 2020. Currently, he is a researcher and lecturer at Telkom University Indonesia. His research interests include biosignal processing, artificial intelligence, and biomedical engineering. He can be contacted at email: hilmanfauzitsp@telkomuniversity.ac.id.

Ziani Said is a professor at the Department of Electrical Engineering at Hassan II University (ESTC) in Casablanca, Morocco. He is with also Department of Health Technologies Engineering, Research Group in Biomedical Engineering and Pharmaceutical Sciences, ENSAM, Mohammed V University, Agdal, Morocco. His research interests include digital design, industrial applications, industrial electronics, industrial informatics, power electronics, motor drives, renewable energy, FPGA and DSP applications, embedded systems, adaptive control, neural network control, automatic robot control, motion control, and artificial intelligence. He is a senior member of IEEE with member/customer number: 98711129. He can be contacted at email: said.ziani@univh2c.ma or ziani9@yahoo.fr.