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Artificial Neural Network Application for Sepsis Prediction: A Preliminary Study

A K Faizin[1,*], **W Saputro**[1], **R D Issafira**[1], **L Edahwati**[1], **W D Lestari**[1], **T P Sari**[1], **N Adyono**[1],

[1] Department of Mechanical Engineering, Faculty of Engineering, University of Pembangunan Nasional Veteran Jawa Timur, 60294, Indonesia

*Corresponding e-mail: ahmad.khairul.tm@upnjatim.ac.id

Abstract. Sepsis is one of the leading causes of mortality in hospitalized patients. It is very difficult to find the symptoms of sepsis because of their similarity to the symptoms of other diseases. This paper aims to deliver an artificial neural network implementation in medical decisions support. This study tries to predict sepsis and healthy patient based on vital signs such as heart rate, systolic blood pressure, and diastolic blood pressure taken from the MIMIC-III clinical database. There were several extraction processes applied to vital sign signals such as using the statistical tools, discrete wavelet transforms, and Hilbert-Huang Transform. The ANN algorithm predicts the sepsis patient with 96.7% of accuracy. However, based on the medical requirement for artificial intelligent implementation, this result does not satisfy the requirement as the false positive error is 2.9%.

Keyword: Sepsis, Artificial Neural Network, Discrete Wavelet Transform, Hilbert-Huang Transform.

1. Introduction

The human body normally releases chemicals into the bloodstream when an infection occurs. The system responsible for this action is called the immune system. However, there is an abnormal condition in which our immune system releases large amounts of chemicals to eliminate infection. This imbalance condition results in not only elimination of infection but also damage to internal organs. This condition is a potentially life-threatening condition called Sepsis.

It is very difficult to find the symptoms of sepsis because of their similarity to the symptoms of other diseases. This can lead to a wrong diagnosis for another serious illness, not sepsis. Based on previous studies, the values of systolic blood pressure (SBPV) and diastolic blood pressure (DBPV) have a positive correlation that can be used to distinguish symptoms. Correlation analysis showed that patients with suspected sepsis had scores that were significantly correlated with SBPV and DBPV ($P<0.01$, $r=0.732$ and $P<0.01$, $r=0.762$). SBPV and DBPV were correlated with cortisol (COR) ($P=0.018$ and $r=0.318$; $P=0.008$ and $r=0.353$ respectively) (Pandey et al., 2014). In order to reach the best diagnosis, doctors need to record sensing the variability of the patient's blood pressure over a period that varies from a few hours to several weeks.

A common method for extracting data in septic patients is to use a photoplethysmogram (PPG). The PPG signal is obtained using a pulse oximeter that illuminates the skin and measures changes in light absorption. PPG signals contain a lot of useful information about the cardiovascular system such as blood pressure, heart rate, and other heart rate components of the cardiac cycle. Due to the signal, PPG is generated by a non-invasive method, so the quality of the PPG signal can be affected by many factors, such as subject movement and the main causes of baseline wandering and motion artifacts. In addition, 50 Hz power line interference is also a problem for PPG signal measurement. So, pre-processing via signal processing and analysis techniques is an important step for PPG signal analysis.

Previous research has been carried out to overcome this problem, where the problem associated with pulse signals is the unwanted interference associated with it, so an approach for de-noising signals based on wavelets is carried out [1]. Diagnosing sepsis based on the analysis of statistical data derived from Wavelet Decomposition is difficult because it depends on the subjectivity of the doctor how long the observation data is collected. An artificial neural network (ANN) has been introduced to support physician decision-making [2]. According to [3], the Fourier transform is not suitable to be applied to medical signals such as PPG signal due to the blood pressure non-stationary nature. Therefore, rather than the Fourier transform, discrete wavelet transform (DWT) decomposition is more suitable for analyzing non-stationary signals [3]. In this study, the Hilbert-Huang Transform (HHT) based on empirical mode decomposition (EMD) is proposed to analyze nonstationary signals such as heart rate and blood pressure [4].

The objective of this study is to implement an artificial neural network for sepsis prediction based on heart rate and blood pressure. In addition, the feature extraction using statistical tool, wavelet based analysis, and time-frequency domain analysis.

2. Research Method

2.1 Data Set

This work uses the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC)-III clinical dataset [5], compiled from the Beth Israel Deaconess Medical Center (BIDMC) in Boston. In this preliminary study, we only used four patient datasets, that are two datasets with sepsis disease and two datasets for healthy patients. In addition, the vital signs that were analysed including heart rate, systolic blood pressure, and diastolic blood pressure.

2.2 Feature Extraction

The block diagram of the feature extractions process is shown in Figure 1(a). The dataset consists of the heart rate (HR), systolic blood pressure (SBP), and diastolic blood pressure (DBP) are analysed by using three methods. These methods are statistical tools, discrete wavelet transform, and time-frequency domain analysis. The statistical analysis used the standard deviation (STD) and root means square (RMS). The wavelet analysis used discrete wavelet transform (DWT). The time-frequency domain analysis used is Hilbert-Huang Transform based on empirical mode decomposition (EMD). Finally, the twenty-one (21) features are generated through these analysis methods (see Figure 1). These features will be input datasets in the machine learning algorithms (see Figure 1(b)). The feature extraction process and all calculations are carried out in MATLAB R2019b.

2.3 Prediction Algorithm

The artificial neural network (ANN) is used as the prediction algorithm based on the extracted features from the feature extraction methods as described above. The artificial neural network consists of three layers with 21 input nodes, 10 hidden nodes, and 1 output node (see Figure 2). The scaled conjugate gradient (SCG) algorithm is used in the training process. The scaled conjugate gradient (SCG) algorithm, developed by Moller [6], is based on conjugate directions, but this algorithm does not perform a line search at each iteration, unlike other conjugate gradient algorithms which require a line search at each iteration. Making the system computationally expensive. This algorithm was designed to avoid the time-consuming line search during the training process. For validation and test performances, the crossentropy algorithm is used. This artificial neural network (ANN) was conducted using MATLAB R2019b.

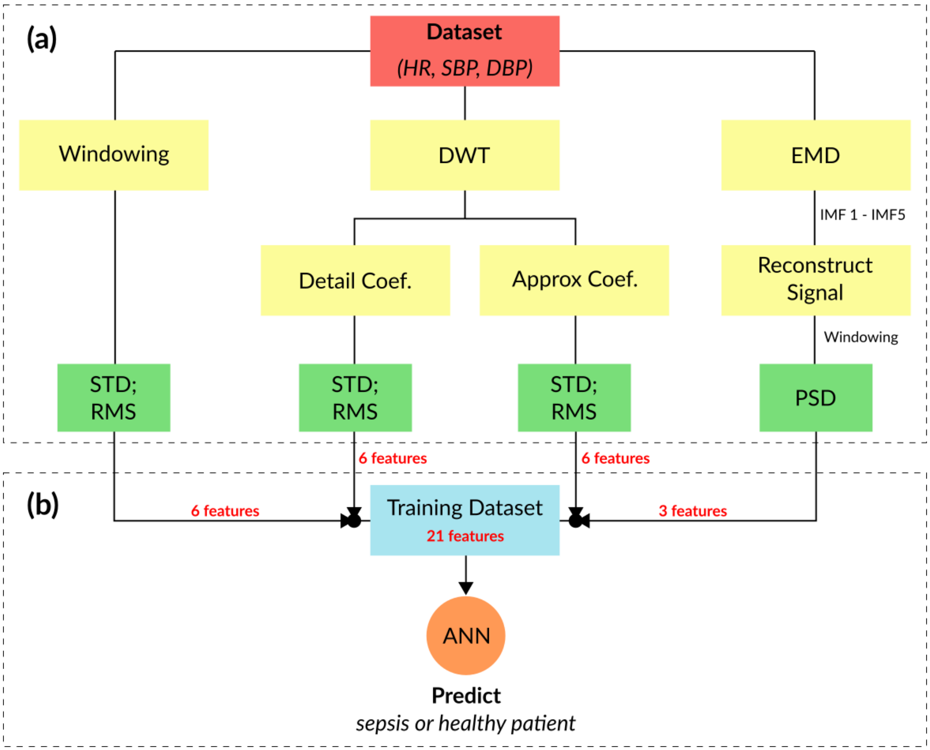

Figure 1. (a) The features extraction procedures. (b) Input dataset and ANN schematic position in sepsis prediction.

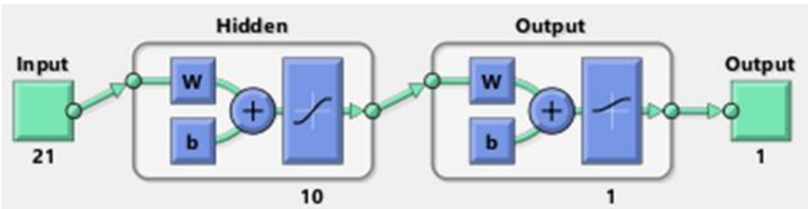

Figure 2. The layer configuration of artificial neural network. Inputs are inserted into the input layer, and each node in hidden layer provides an output value via an activation function.

3. Results and Discussions

In this study, prediction of sepsis condition was conducted using artificial neural network (ANN). The machine learning algorithm is applied into vital signs such as heart rate, systolic pressure, and diastolic pressure data. The features of these data are extracted by using statistical, wavelet, and time-frequency domain analyses. The features extraction generates in 21 features to be used as input data of the artificial neural network algorithm. Firstly, statistical analyses are applied to these data by using standard deviation and root mean square and it generates 6 features. Secondly, a discrete wavelet transform is applied to these data by employing 1 level of Daubechies3 (db3 function in MATLAB) wavelet. Then the approximated and detailed coefficients both are analyzed by using standard deviation and root mean square and generates about 12 features. Thirdly, empirical mode decomposition is applied to these data. Then power spectral density (PSD) is applied to the reconstructed data and generates 3 features. The Figure 1 describe the block diagram process of sepsis prediction.

In this preliminary study, we proposed a feature extraction method that was employed Hilbert-Huang Transform based on empirical mode decomposition (EMD) in order to increase ANN prediction

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performance. The EMD decomposed heart rate signal, systolic pressure signal, and diastolic pressure signal into several variated sub-signal that have many types of frequencies so-called intrinsic mode functions (IMF), and obtain instantaneous frequency data. In this study, IMF2 to IMF5 are used to reconstruct the main signal since the remain IMFs may contain noisy and unwanted properties. For instance, IMF2 to IMF5 of heart rate signal from healthy patient and patient with sepsis condition is shown in Fig. 3. The IMFs show that healthy patient and patient with sepsis conditions are unable to be distinguished, therefore these IMF signals cannot be used directly as the artificial neural network inputs. Furthermore, the power spectral density (PSD) is selected as the further analysis of the reconstructed signal. As a result, healthy patient and patient with sepsis condition can be distinguished clearly (shown in Fig. 4). The heart rate signal of patient with sepsis condition tends to emerge high and fluctuating PSD value, perhaps due to the bacteria onset which leads to the sepsis disease.

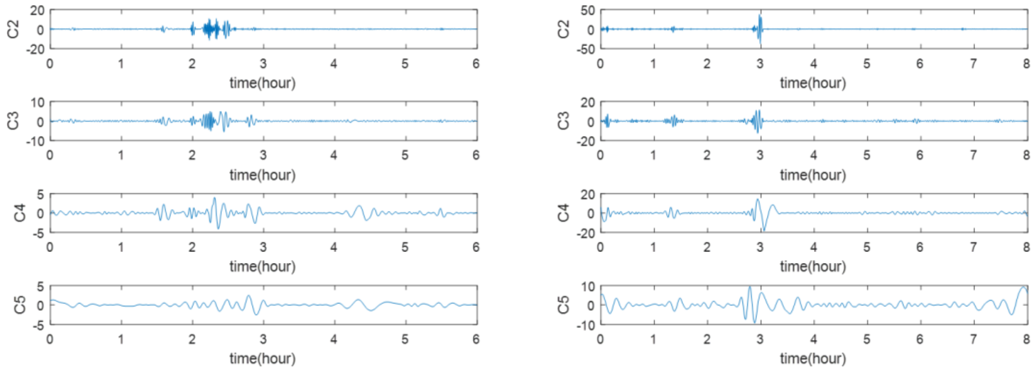

Figure 3. (Left) IMF2 to IMF5 of the heart rate signal of healthy patient. (Right) IMF2 to IMF5 of sepsis patien

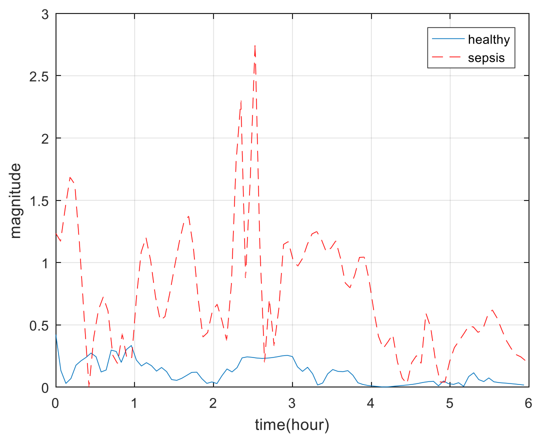

Figure 4. The power spectral density of the reconstructed heart rate signal

Figure 5 shown the ANN performance in term of training, validation, and test parts. The results show the training, validation, and test accuracies are 96.6%, 93.8%, and 100% respectively. These results describe the artificial neural network capability in predicting sepsis conditions and healthy patients. However, in terms of medical implementations, the desired performance should have a false positive to be less than 0.5 %. So that the false diagnosis which risking the patient’s condition can be avoided. According to our training and validation confusion matrix, the false positive is not satisfying the medical requirements.

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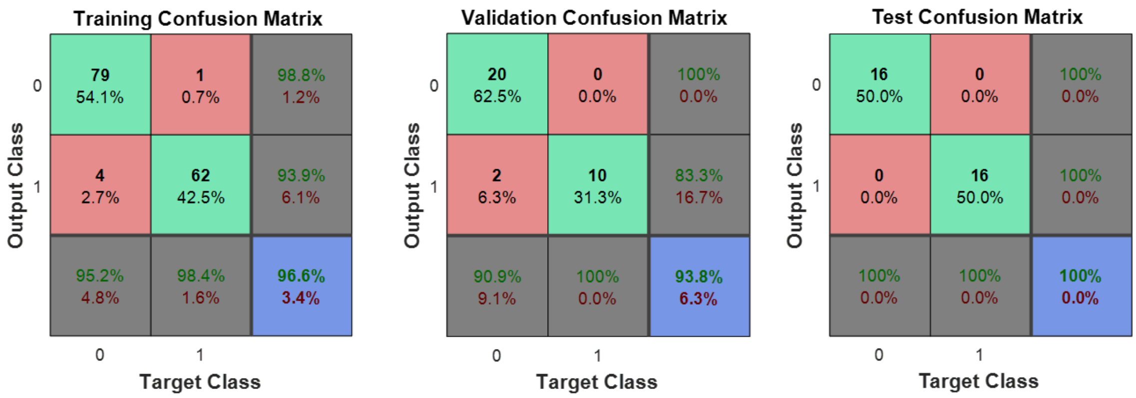

Figure 5. ANN training, validation, and test performance results

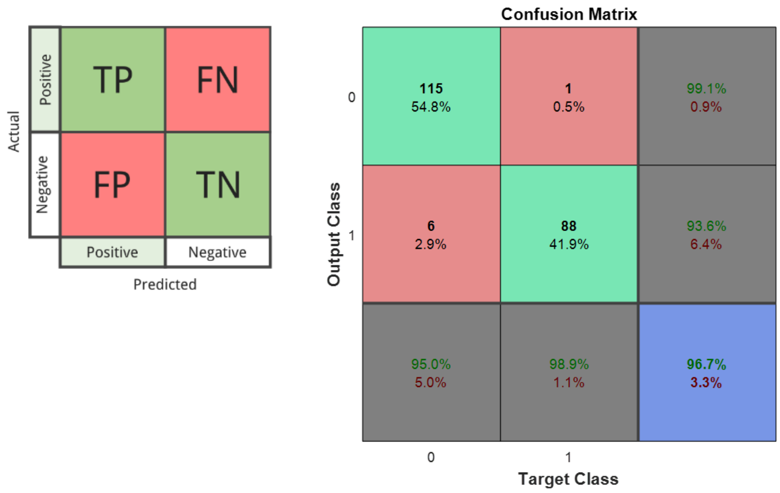

Figure 6. Overall ANN performance results

Overall results of ANN performances are shown in Figure. 6. The ANN performances yield a 96.7 % accuracy and yield 2.9% in terms of false positive. As described, the false positive is an important performance indicator in disease screening such as sepsis disease. Yet in this preliminary study, the false positive is larger than 0.5%, probably requires a huge amount of data for future studies. In terms of prediction sepsis prediction, this preliminary study has proved that an artificial neural network can be used in medical support decisions.

4. Conclusion

The artificial neural network algorithm is applied to predict patients with sepsis conditions. The feature extraction using empirical mode decomposition based on Hilbert-Huang Transform has proved convenient to extract valuable information from the nonstationary signals. The prediction yields 96.7 % of accuracy with 2.9 % false positive. However, based on the medical requirement for artificial intelligent implementation, this proposed method does not satisfy the requirement as the false positive error is 2.9 %, which mean improvement are needed, especially in improvement the number of dataset in order to train the ANN to has a better performance.

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References

[1] Joseph, G., Joseph, A., Titus, G., Thomas, R.M. and Jose, D 2014 *Annual international conference on emerging research areas: Magnetics, machines and drives* (AICERA/iCMMD) pp. 1-5
[2] Schuh, C.J. 2015 *Annual Meeting of the North American Fuzzy Information Processing Society* pp. 650-654
[3] Fan, P., Peiyu, H., Shangwen, L. and Wenfeng, D. 2015 *IEEE International Conference on Digital Signal Processing (DSP)* pp. 283-286
[4] Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C. and Liu, H.H. 1998. *Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences* pp.903-995
[5] Johnson, A.E., Pollard, T.J., Shen, L., Li-Wei, H.L., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L.A. and Mark, R.G. 2016 *MIMIC-III, a freely accessible critical care database*. *Scientific data*, *3*(1) pp.1-9
[6] Moller, M.F. 1993 *A scaled conjugate gradient algorithm for fast supervised learning*. Neural networks, *6*(4) pp.525-533.
[7] Pandey, N.R., Bian, Y.Y. and Shou, S.T. 2014 *World journal of emergency medicine, 5(1),* p.42