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Abnormality Heartbeat Classification of ECG Signal Using Deep Neural Network and Autoencoder

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***Abstract*— Electrocardiogram (ECG) is a device used by healthcare practitioners to monitor and processing of patient health data so can detect abnormality cardiovascular disease. Continuous heart supervision generates large amounts of data and analyzes this large data need classification method. This Paper exposes the classification of heartbeat abnormality based on the ECG signal by using Deep Neural Network (DNN). Three preprocessing stages of the ECG signal are applied before the classification process, which is segmentation, normalizing using normalize bound, and feature extraction by using Autoencoder. The results show that the applied method gets an outstanding accuracy about 99.22% and sensitivity about 98.03%.**

Keywords—ECG, abnormal, classification, autoencoder, Deep Neural Network

I. Introduction

Heart disease needs more monitoring by health care practitioners. Monitoring and processing of patient heart health data can detect various cardiovascular diseases and also prevent convenient health problems. However, both the monitoring and processing of the patient's heart data continuously is troublesome. Continuous heart supervision generates large amounts of data and analyzes this large data using conventional methods that it is very difficult to do [1]. Heart disease researchers are not only about community protection, but also a motivating technological challenge on the development of scientific technologies. A device that can produce a recording monitoring of heart health in the form of electrocardiogram (ECG) [2].

ECG can detect and categorize different waveforms and morphologies in the signal [3]. ECG signals have three different waveforms on each cardiac circle, i.e. P wave, QRS complex and T-wave under normal conditions [4]. P Wave represents atrial depolarization, the QRS wave represents ventricular depolarization and T wave represents the repolarization of the ventricle [5]. In certain cases, the ECG form changes T waveform, i.e., ST interval length, ST elevation, wherein this morphology causes cardiac abnormality [6]. Abnormal heart rate detection relies on ECG signal inspection during the sufficient sampling process. Sampling process requires adequate data that can be extracted into a feature. Such a feature can result in accurate measurements to detect abnormality ECG signals [7].

In the past few years, ECG signal detection abnormality has challenged many researchers. The approach applied is the classification process sourced from the data in the form of rhythm and beat. The beat form has been used in various studies with good results as a classification data. Deep learning is a method to classification process. Method is implemented using deep learning approaches, such as the novel Hybrid Neural Network [8], a combination of neural network [9], Artificial Neural Network [7], Deep Neural Network (DNN) [10][11].

The DNN method is used within supervised machine learning techniques using three or more layers [12][11]. DNN has been used for a lot of research such as image processing, face recognition, particularly for ECG signal classification [10]. Excess DNN method on the ECG classification is to extract features by analyzing data and not forcing features based on preprocessing results [13]. In preprocessing, the extraction feature is an important step in the learning process to get good and powerful features [14]. In research [10][14] indicates that the Autoencoder method to improve the results of classification accuracy.

In this paper, we propose a normal and abnormal ECG signal classification with DNN method. Each data submitted uses beat as the process data. We propose the DNN method and the extraction feature with Autoencoder.

II. Experimental Method

In this study proposed five stages in the abnormal classification of ECG signals (Fig. 1), Data Preparation, preprocessing, feature extraction, classification (training, testing and validation data) and complete with the evaluation model. Evaluation model method consist of accuracy, sensitivity, specificity, positive predictivity, f1 score, and error ratio.

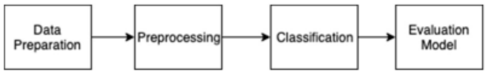


Fig. 1. Research stage Diagram block Abnormal detection of ECG signals.

A. Data Preparation

The labeled ECG dataset used is the MIT-BIH due database sourced from physionet.org developed by the Massachusetts Institute of Technology (MIT) and BIH (Beth Israel Hospital) containing 48 records of electrocardiogram through patient observation Supported by MIT [15][3]. Recordings are digitized at 360 samples per second per channel with the 11-bit resolution with a range of more than 10 mV [16][10]. This database is accordingly suitable for evaluating the performance and accuracy of the hardware developed for a wide spectrum of heart disease [17].

ECG Record is a compilation of various waveforms, artifacts, ventricular complexes, and abnormal conduction. Each record includes an annotation file where each ECG beat is labeled by more than two cardiologists [16]. This Label related to as the truth annotation and applied to be the evaluation model in section E. Result. Here allows a serial detection of different components of ECG signals in detecting abnormal signals.

B. Preprocessing

The first process in this study is preprocessing to eliminate various interruptions from the original ECG signal. The process of noise elimination can be used to different methods [18]. Preprocessing is perfomed before the classification process. The purpose of this process is to improve system efficiency. Preprocessing consists of segmentation, normalizing data, and feature extraction.

1) Segmentation

The original dataset used ECG signal was recorded with a sampling frequency of 360 Hz and the length of each given record is 650,000 nodes will be done segmentation process from rhythm signal to beat. The signal segmentation process starts with identifying the distance between 2 peaks R on the rhythm of the original signal (Fig. 2), if it has found the position of R to R then it can determine the Q wave and S will then be in getting the QRS wave, so it can be determined P wave and T wave [19].

In the process, the rhythm segmentation converts to beat signal is determined from 0.25 seconds before the peak of R called the Duration, T-1. and 0.45 seconds after the R peak called the duration, the T-2. (Fig. 2). The result of the accumulated length of 1 heartbeat is 0.7 seconds or 252 nodes that include P waves, complex QRS, and T-waves [20].

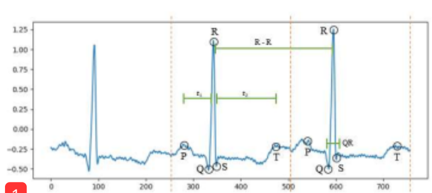
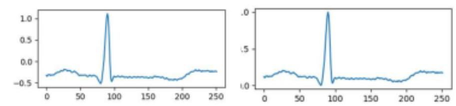


Fig. 2. Segmentation process from rhythm to beat signals

2) Normalization Data

Normalization data is used to change the value of the amplitude of signals that have been segmented to have a consistent amplitude value without changing morphology [21]. In this study, the normalization method of data used was Normalize Bound. Normalize Bound changes the lower limit value (lower bound) and the upper limit (upper bound) at the amplitude of the signal to a smaller range without altering the pattern or shape of the initial signal. The segmented data is given the upper and lower limits of 0 and 1 to the upper limit (Fig. 3). Once all data has been grouped by the upper and lower limits. So, each new data is obtained during Normalize Bound using (1) with the property mentioned above. This scale adjustment is required for initial input value in stage of feature extraction and classification. Both processes use the DNN method to calculate the weight with fiture of ECG signal. Data is ready to extract its features after all data stored in Normalize Bound.



(a) (b)

Fig. 3. Changing signal range without changing the morphological form raw (a) to normalized (b) signal

Normalize bound delivers the same signal range results. Scale adjustments to the signal range using the Normalized Bound equation (1) as follows:

$$f(x) = x * coef - (x_{mid} * coef) + mid \quad (1)$$

where

$$coef = \frac{ub - lb}{x_{max} - x_{min}}$$

$$x_{mid} = x_{max} - \frac{x_{max} - x_{min}}{2}$$

$$x_{max} = max(x)$$

$$x_{min} = min(x)$$

$$mid = ub - \frac{ub - lb}{2}$$

3) Feature Extraction

The extraction feature is applied in a feature-taking process characteristic that can represent the characteristics of a normalized beat [22]. In feature extraction method, [10] implies that processing using Autoencoder can improve accuracy. Preprocessing in this study used model Autoencoder. The Autoencoder (2) [23] architecture used in the Input layer and the Output layer has 252 features that amount to a length of 1 heart rate signal.

$$L(x, g(f(x))) \quad (2)$$

In the first hidden layer used Rectified Linear Unit (ReLU) activation function (3). Then the Output layer used Sigmoid activation function (4).

$$f(x) = \begin{cases} 0 \; for \; x \leq 0 \\ x \; for \; x > 0 \end{cases} \tag{3}$$

$$f(x) = \sigma(x) = \frac{1}{1+e^{-x}} \tag{4}$$

Model COMPILE on Autoencoder is require of two arguments, i.e. Optimization and Loss Function. The optimization used in this Autoencoder is Adaptive Moment Estimation (ADAM) [24]. Then the function of loss function used in this model Autoencoder is main squared error.

Creating architecture and drafting the Autoencoder before training data, require at least 3 argument, i.e. there is data worked for training, the epoch, and batch size. The epoch was performed at 400 times and the Batch Size was 64.

TABLE I. MODEL OUTPUT EXTRACTION FEATURE AND CLASSIFICATION INPUT DNN

Model	Number of hidden layers	Number of nodes on the layer	Feature input DNN
1	3	[252, 126, 252]	126
2	5	[252, 126, 63, 126, 252]	63
3	7	[252, 126, 63, 32, 63, 126, 252]	32
4	9	[252, 126, 63, 32, 16, 32, 63, 126, 252]	16

This study proposes 4 Autoencoder models that each model have a variation in the number of Hidden Layer features. The Autoencoder architecture consists of four models i.e. 3, 5, 7, 9 hidden Layer (Table I). Every model has difference in the feature-length of the output feature, i.e. 126, 63, 32, 16.

C. Classification

The classification method applied in this study is DNN. The DNN method relates to the Deep Learning section as features are processed using multiple layers and use the Back-Propagation algorithm [25].

Like the Autoencoder, the DNN is also sequential-shaped because it is essentially a Neural Network. The DNN Model used in this research has architecture of 5 layers in total where 2 of them are Input Layer and Output Layer, the rest are 3 Hidden layers (Fig. 4). Input layer adjust the feature-length of output feature extraction. The experiment runs 4 different model classification.

Within Input Layer, there is a length of x that refers to the length of each 1 signal feature. Value x represents a feature-length that corresponds to the length of the output feature extraction (Table 1). In Output Layer, there is 1 node that shown the number of classes is classified. The Hidden layer worked on this model has the same number of nodes. Meanwhile middle hidden layers tend to have larger numbers. 1st and 3rd Hidden layer has the number of nodes as much as 100 nodes. Every node is equal to 1 length Features.

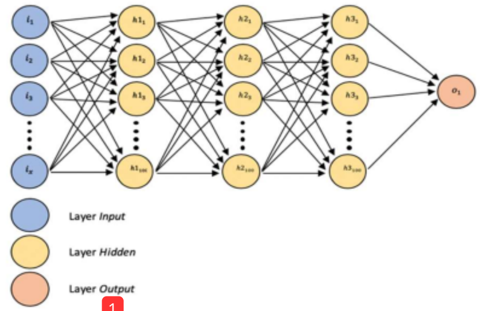


Fig. 4. DNN Classification Architecture

On this classifications, the model classification employed Rectified Linear Unit (ReLU) activation function on all Hidden layers and the activation function Softmax (5) on the Output Layer [26]. Along with the function of loss applied, there are two functions, the function loss Categorical Crossentropy [27] and the function loss Mean Squared Error, and Optimizer ADAMAX [24]. Equation of Softmax activation function using:

$$f_i(\vec{x}) = \frac{e^{x_i}}{\sum_{J=1}^{J} e^{x_j}} \text{ for } i = 1, \ldots, J \tag{5}$$

At this stage, the architecture of the DNN model is finished and available for training data. The features used for training are already extracted in the feature extraction stage. The label used is the label that has been sorted at the data preparation stage. Before this Model was in-Training, all feature data and labels were divided into 72:18:10 data respectively (Fig. 6), of which 72 was the percentage of the number of features and labels used for the Training Model, 18 was the percentage of the number of features and labels used For Testing, while 10 is the percentage of the number of features and labels used for Validation. This Model was in-Training as much as 150 Epoch and batch size of 48.

In the Training stage, the Model of the Autoencoder can be used to reconstruct the signal. To reconstruct the signal it takes 2 stages, in the first step is predicted the input signal on the Hidden layer or is also called an encoder. In the second stage is predicted the output signal from the Hidden layer on the Output layer or also called the decoder. The predicted result of the Output layer is the signal that has been in the reconstruction. Once acquired signal encoder signal that will be used as a feature for classification.

The process of splitting data in the classification phase is done by separating the features along with the label into 3 parts, namely for Training, Testing, and Validation. The Division of data is 72% Training data, 18% Testing data, and 10% Validation data. This feature is separated randomly but still pay attention to the number of labels of each class, to be obtained the same comparison for Each class. The technique used to separate these two data is the train test split.

DNN models already in-Training will be found accuracy model and model loss in the evaluation model. With both values, it can be the measured performance of the Model created. To measure the performance of this model will be described in the evaluation Model.

D. Evaluation Model

Performance of models made using Confusion Matrix (matrix of Confusion). Before being able to get the Confusion Matrix should first predict the class of the Testing feature to get the value of the Confusion Matrix.

Following obtaining the Confusion Matrix value can now measure the performance of this Model. There are two stages to get the final performance value. First, get the True positive (TP), False positive (FP), False negatives (FN), and True negative (TN). Secondly, using equation from confusion matrix to calculate it and gets Accuracy (6), Sensitivity (8), Specificity (10), Positive Predictivity (7), F1 Score (9), Error Rate (11) [28]. Here are the equations of the measuring instruments above.

Accuracy (ACC). $= \frac{tp+tn}{tp+fp+fn+tn}$ (6)

Positive Predictivity (PP) $= \frac{tp}{tp+fp}$ (7)

Sensitivity (SEN) $= \frac{tp}{tp+fn}$ (8)

F1 Score (F1) $= \frac{(\beta^2+1)tp}{(\beta^2+1)tp+\beta^2 fn+fp}$ (9)

Specificity (SPE) $= \frac{tn}{fp+tn}$ (10)

Error Ratio (E). $= \frac{\sum_{i=1}^{l} \frac{fp_i+fn_1}{tp_i+fp_i+fn_i+tn_i}}{l}$ (11)

III. Result and Discussion

The experiment was done by performing a difference in the number of hidden layers in the extraction process of the feature that became input in the DNN classification process. Analysis working with Python. The experiment has 4 models from 3, 5, 7 and 9 hidden layers (Table I) during classification process. During the classification, the process of training and testing of data is 90% of the total amount of data, which is divided into 80% training and 20% testing. The remaining 10% of the total data for evaluation. If the overall data analysis is calculated to be 72% training, 18% testing, and 10% evaluation.

Each model that has been performed shows the results of a different evaluation model (Table III) in each model. Confusion Matrix (Table II) can be used to calculate the evaluation model.

TABLE II. Confusion Matriks

Model	TP	FP	TN	FN
1	1894	49	9276	38
2	1879	64	9281	33
3	1888	55	9263	51
4	1809	134	9251	63

There are some studies about abnormality ECG signal that using neural network methods. Dokur uses a novel hybrid neural network method with a measurement of 96% [8]. Guler uses neural network accuracy combination method of 96.94% [9]. Al Masri Classification of normal and abnormal heartbeat ECG signals using Artificial Neural Network [7] accuracy of 98.70%. Kim used the method of DNN accuracy of 98.31% [11]. These studies shown good accuracy measurement using DNN method. The result of this experiment (Table III) presents the best measurement. The best model evaluation i.e. models 1, 2 and 3 show excellent results above 99% (Table III). The evaluation results indicate that the difference model hidden layer greatly affects the results of the evaluation model accuracy.

The evaluation model results of each model have different results (Table III). In Table III, shows the results of measurements that tend to decline starting from the first model by using the model features extraction 3 hidden layer to the fourth model where using model 9 hidden layer. It can also be seen from each measurement, where the highest result is on the first model Accuracy 99.22%, Sensitivity 98.03%, Specificity 99.47%, Positive Predictivity 97.47%, F1 Score 97.47% and Error ratio 0%. Followed by the second model Accuracy 99.13%, Sensitivity 98.27%, Specificity 99.31%, Positive Predictivity 96.70%, F1 Score 97.48% and Error ratio 0%.

TABLE III. Model Evaluation

Model	ACC (%)	SEN (%)	SPE (%)	PP (%)	F1 (%)	E (%)
1	99.22	98.03	99.47	97.47	97.47	0.00
2	99.13	98.27	99.31	96.70	97.48	0.00
3	99.05	97.36	99.40	97.16	97.26	0.00
4	98.24	96.63	98.57	93.10	94.83	0.01

Its short-length output features affect the results of testing and validation in the DNN classification process. These results are shown in (Fig. 5-8) in accuracy and model loss graphs. The graph presents the difference starting from the first model by using the model's Extraction feature 3 hidden layer to the fourth model where it uses the Model 9 hidden layer. Testing results tend to approach the best value or approach value 1, on the fourth model with 9 hidden layers of extraction feature and 16 input features in the DNN classification.

DNN by applying different feature-length inputs shows various evaluation model values but yields varying measurement values. In the Model 3 models of measurement hidden layer provides the highest accuracy value reached 99.22%. Followed by a model 5 hidden layer accuracy about 99.13%, 7 hidden layer accuracy about 99.05% and 9 hidden layer accuracy 98.24%.

IV. Conclusion

Based on the results of 4 model experiment, shown at the Evaluation Model measurement (Table III). Authors can draw conclusions that the best model on the four following experiments from 4 model are owned by the first experiment

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by using the Model 3 hidden Layer on the extraction feature and the 126 input feature in the DNN classification. Evaluation model of the first model (Table III) accuracy value about 99.22%, and sensitivity about 98.03% which shows outstanding measurement results.

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REFERENCES

[1] O. Castro-Lopez, D. E. Lopez-Barron, and I. F. Vega-Lopez, "Next-generation heartbeat classification with a column-store DBMS and UDFs," *J. Intell. Inf. Syst.*, Apr. 2019.

[2] P. M. Kumar and U. Devi Gandhi, "A novel three-tier Internet of Things architecture with machine learning algorithm for early detection of heart diseases," *Comput. Electr. Eng.*, 2018.

[3] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, "ECG Heartbeat Classification: A Deep Transferable Representation," in *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, 2018, pp. 443–444.

[4] W. N. Evans, R. J. Acherman, G. A. Mayman, R. C. Rollins, and K. T. Kip, "Simplified pediatric electrocardiogram interpretation," *Clinical Pediatrics.* 2010.

[5] N. Maglaveras, T. Stamkopoulos, K. Diamantaras, C. Pappas, and M. Strintzis, "ECG pattern recognition and classification using non-linear transformations and neural networks: A review," in *International Journal of Medical Informatics*, 1998.

[6] R. Tung and P. Zimetbaum, "Use of the Electrocardiogram in Acute Myocardial Infarction," in *Cardiac Intensive Care*, 2010.

[7] E. Al-Masri, "Detecting ECG Heartbeat Abnormalities using Artificial Neural Networks," in *2018 IEEE International Conference on Big Data (Big Data)*, 2018, pp. 5279–5281.

[8] Z. Dokur and T. Ölmez, "ECG beat classification by a novel hybrid neural network," *Comput. Methods Programs Biomed.*, 2001.

[9] İ. Güler and E. D. Übeylı˙, "ECG beat classifier designed by combined neural network model," *Pattern Recognit.*, vol. 38, no. 2, pp. 199–208, Feb. 2005.

[10] M. M. Al Rahhal, Y. Bazi, H. AlHichri, N. Alajlan, F. Melgani, and R. R. Yager, "Deep learning approach for active classification of electrocardiogram signals," *Inf. Sci. (Ny).*, vol. 345, pp. 340–354, Jun. 2016.

[11] J. H. Kim, S. Y. Seo, C. G. Song, and K. S. Kim, "Assessment of Electrocardiogram Rhythms by GoogLeNet DNN Architecture," *J. Healthc. Eng.*, 2019.

[12] F. Firdaus, M. Anshori, S. P. Raflesia, A. Zarkasi, M. Afrina, and S. Nurmaini, "DNN Structure to Improve Individual Performance based Author Classification," *Comput. Eng. Appl. J.*, vol. 8, no. 1, pp. 77–83, Feb. 2019.

[13] J. Masci, A. Giusti, D. Ciresan, G. Fricout, and J. Schmidhuber, "A fast learning algorithm for image segmentation with max-pooling convolutional networks," in *2013 IEEE International Conference on Image Processing, ICIP 2013 - Proceedings*, 2013.

[14] S. Nurmaini, R. U. Partan, W. Caesarendra, and T. Dewi, "applied sciences An Automated ECG Beat Classification System Using DNN with an Unsupervised Feature Extraction Technique."

[15] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 664–675, Mar. 2016.

[16] R. G. Mark, P. S. Schluter, G. Moody, P. Devlin, and D. Chernoff, "ANNOTATED ECG DATABASE FOR EVALUATING ARRHYTHMIA DETECTORS.," in *IEEE/Engineering in Medicine and Biology Society Annual Conference*, 1982.

[17] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 3, pp. 45–50, 2001.

[18] H. M. Rai, A. Trivedi, and S. Shukla, "ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier," *Measurement*, vol. 46, no. 9, pp. 3238–3246, Nov. 2013.

[19] E. J. da S. Luz, W. R. Schwartz, G. Cámara-Chávez, and D. Menotti, "ECG-based heartbeat classification for arrhythmia detection: A survey," *Comput. Methods Programs Biomed.*, vol. 127, pp. 144–164, Apr. 2016.

[20] Q. Qin, J. Li, L. Zhang, Y. Yue, and C. Liu, "Combining Low-dimensional Wavelet Features and Support Vector Machine for Arrhythmia Beat Classification," *Sci. Rep.*, vol. 7, no. 1, p. 6067, Dec. 2017.

[21] A. K. Jain, Jianchang Mao, and K. M. Mohiuddin, "Artificial neural networks: a tutorial," *Computer (Long. Beach. Calif).*, vol. 29, no. 3, pp. 31–44, Mar. 1996.

[22] A. E. Vincent and K. Sreekumar, "A survey on approaches for ECG signal analysis with focus to feature extraction and classification," in *2017 International Conference on Inventive Communication and Computational Technologies (ICICCT)*, 2017, pp. 140–144.

[23] I. Goodfellow, Y. Bengio, and A. Courville, "Deep Learning TOC," *Deep Learn. B.*, 2017.

[24] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," pp. 1–15, 2014.

[25] S. Nurmaini, P. R. Umi, R. M. Naufal, and A. Gani, "Cardiac arrhythmias classification using DNN and principle component analysis algorithm," *Int. J. Adv. Soft Comput. its Appl.*, 2018.

[26] G. Sannino and G. De Pietro, "A deep learning approach for ECG-based heartbeat classification for arrhythmia detection," *Futur. Gener. Comput. Syst.*, vol. 86, pp. 446–455, Sep. 2018.

[27] S. Nurmaini, R. Umi Partan, and M. Naufal Rachmatullah, "Deep classifier on the electrocardiogram interpretation system," *J. Phys. Conf. Ser.*, vol. 1246, p. 012030, 2019.

[28] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, Jul. 2009.

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