Image Based ECG Signal Classification Using Convolutional Neural Network

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Abstract—Electrocardiogram (ECG) analysis is one of the gold standards in diagnosing heart abnormalities. Commonly, clinicians analyze the ECG signal visually by observing the shape, rhythm, and voltage of the signal. Some of them are supported by the application of automatic diagnosis of the ECG device itself. Currently, digital signal processing combined with traditional or advanced machine learning plays an important role in supporting medical diagnosis including ECG diagnosis. However, it is often constrained by the lack of raw data support from most commercial ECG devices. Classification method by processing ECG image can be one way to tackle this problem. Therefore, in this preliminary study, an image-based ECG classification method using a deep learning approach is proposed. The ECG signals analyzed in this study include normal sinus rhythm (NSR), premature ventricular contraction (PVC), and Bigeminy. Convolutional neural network (CNN) with VGG16 architecture has been employed for feature extraction and classification. The simulation results show up to 95% accuracy in detecting ECG abnormalities. The results of this study can be an alternative in detecting ECG abnormalities and can be considered as a supporting diagnosis by the clinician.

Keywords—ECG, classification, image based, deep learning, CNN

1 Introduction

Heart disease is the leading cause of death worldwide [1], and the second leading cause of death in Indonesia [2]. According to World Health Organization (WHO) studies [3], 16% of all deaths worldwide in 2019 are caused by heart disease. This number surpassed the death caused by stroke and respiratory disease globally. Heart disease can be detected from an electrocardiogram (ECG) signal [4]. The signal pattern can then be analyzed to detect heart rhythm abnormalities or irregular heartbeat, also known as arrhythmias.

The cardiologist can use computer-based assessments to help them analyze the ECG signal by visualizing and getting the heart rhythm pattern to detect the abnormality. In addition to processing the ECG signal generated by the device, recently there has been a need to analyze the recorded ECG signals both captured or printed into images. Garg, et al. digitized ECG paper records using image extraction and processing techniques [5]. Using a MATLAB-based algorithm, Gurve, et al. extracted numerical information from ECG signals recorded on grid-standardized papers [6]. Furthermore, Baydoun, et al. with more than 95% of precision proved that it is it possible to utilize machine learning algorithms to identify patterns of heart diseases baed on printed ECG signals [7]. There are several commercial products of ECG devices that have a built-in monitor to show the visualization of the ECG signals. But most of them do not provide access to raw data (signal amplitude value), whereas the existing research primarily uses raw data as input to analyze and detect the abnormality. Processing the ECG signal in image-based analysis can be one of the answers to this problem. Analyzing ECG signals from image-based data is still a challenge today as the accuracy of the conversion results becomes the important key before the classification task is carried out, while many conditions will be considered regarding the visual condition of the recorded data. Moreover, it will be interesting to utilize computer vision and deep learning techniques which are developed rapidly in recent years in solving image-based ECG signal classification problems.

On the other hand, deep learning popularity has risen in recent days due to its remarkable performance in computer vision tasks such as classification [8], [9], object detection [10-12] and segmentation [13]. Beside regular image classification, deep learning also shows its promising result in image related to biomedical areas, likely Xie H. et. al. [14] detecting pulmonary nodules using convolutional neural networks, while Shankar K et.al.[15] use deep learning approaches to detect and classify diabetic retinopathy automatically.

This paper aims to use the image-based signal analysis approach to classify the ECG signal using deep learning to overcome the limited access of raw data. The input data comes from capturing the image of ecg waves from the monitor. We conduct two types of classification scenarios: the first one is binary classification, which classifies normal vs. abnormal class. The second one is multi-class classification involving three categories: normal, premature ventricular contraction (PVC), and Bigeminy.

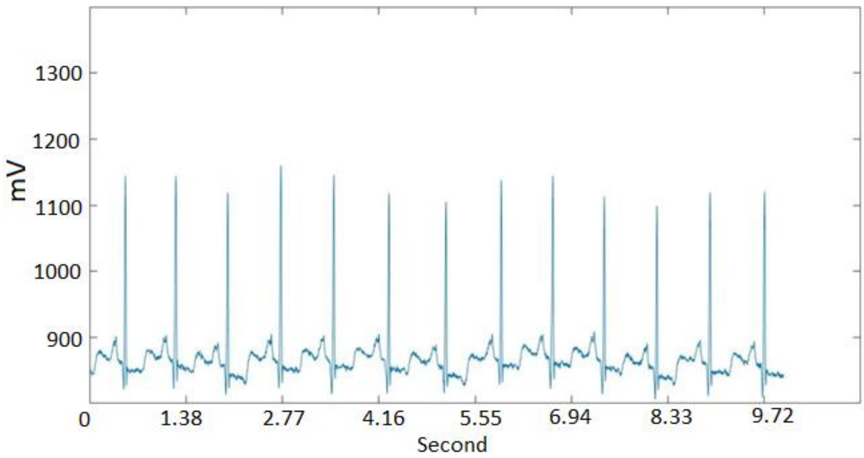
The rest of this paper is organized as follows: related works and proposed methods are provided in Section II and Section III, respectively. Section IV discusses the acquisition of input data, experimental settings, and results. While Section V addresses the summary of this study.

2 Material and methods

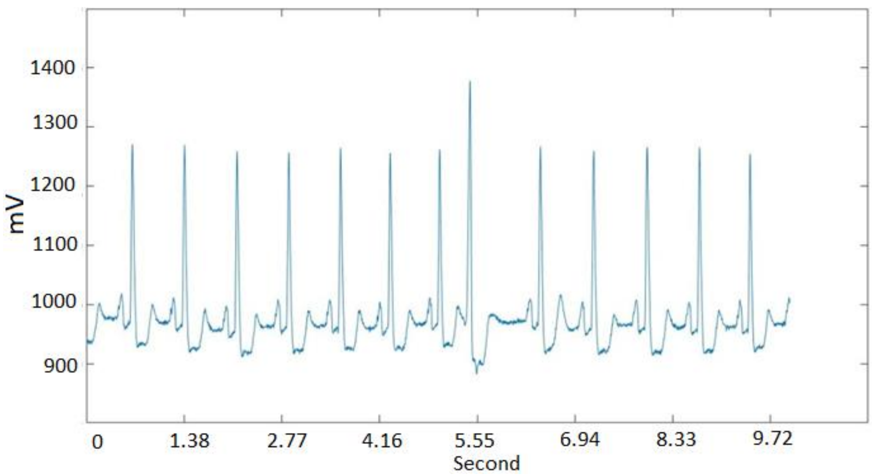
2.1 ECG dataset

The data used in this study is sourced from MIT-BIH Arrhythmia database and publicly available on the PhysioNet service (can be downloaded at http://www.physionet.org). This dataset was first published in 2001 by Moody, et al. in a paper entitled "The impact of the MIT-BIH Arrhythmia database" [16]. The dataset contains 48 half-hour excerpts of two-channel ambulatory ECG recordings. In the data recording process, ECG signals were obtained by involving 45 patients consisting of 19 women aged

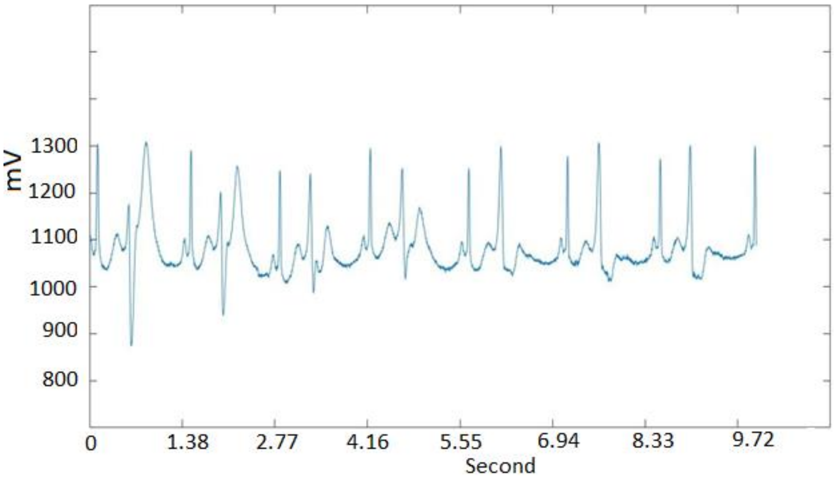
23 to 89 years and 26 men aged 32 to 89 years. The data is labeled with 17 classes consisting of 1 normal sinus rhythm class, 1 pacemaker rhythm class, and 15 classes corresponding to the types of heart abnormalities (at least 10 signal fragments were collected for each abnormality class). The creator of this dataset recorded each ECG signal at a sampling frequency of 360 Hz and a gain of 200 adu/mV. A total of 3,600 samples (ECG signal fragments) with non-overlapping conditions were randomly selected for analysis purposes. Moreover, only signals originating from one lead were used. In this study, three classes of ECG signals were used including normal (NSR), PVC, and Bigeminy as presented in Figure 1.



(a)



(b)



(c)

Fig. 1. ECG signal in image format (a) NSR (b) PVC (c) Bigeminy

2.2 CNN architectures: VGG16

VGG16 [17] is a convolutional neural network model developed by K. Simonyan and A. Zisserman of the Visual Geometry Group, the University of Oxford. It won the ILSVRC2014 (ImageNet Large Scale Visual Recognition Challenge 2014) competition in 2014. The pre-trained VGG16 model achieved 92.7% top-5 test accuracy in ImageNet, a dataset of over 14 million images categorized into 1,000 classes. After all these years, VGG16 is still considered an excellent vision model and becomes the basis for the development of other newer models.

Figure 2 shows the CNN composition on the VGG16 architecture which consists of 16 convolutional and fully connected layers. At the very beginning, it accepts an input image with a size of 224x224 and 3 channels (RGB). Then, the image goes through a number of convolutional layers with 5 times experiencing spatial pooling (max-pooling). In the last part, there is a softmax layer before the output is generated. More detailed VGG16 configuration can be seen in Table 1.

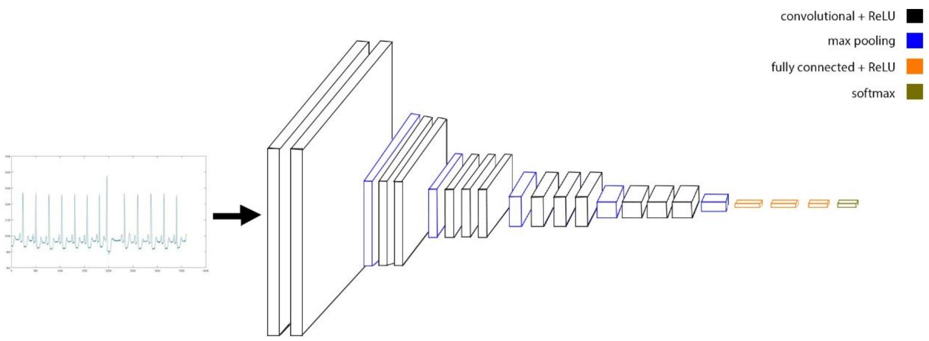


Fig. 2. VGG16 Architecture [14]

Table 1. VGG16's network configuration

ConvNet Configuration: 16 weight layers
Input (RGB image-512)
Convolutional3-64 Convolutional 3-64
Max-pool
Convolutional3-128 Convolutional3-128
Max-pool
Convolutional3-256 Convolutional3-256 Convolutional3-256
Max-pool
Convolutional3-512 Convolutional3-512 Convolutional3-512
Max-pool
Convolutional3-512 Convolutional3-512 Convolutional3-512
Max-pool
FC-4096
FC-4096
FC-1000
Soft-max
Output

The VGG16 architecture has been applied to deep neural network models for a variety of tasks, including malicious software classification [18], kiwifruit detection [19], traffic scene semantic segmentation [20], [21], and weld defect images classification [22], batik classification [23], and fish species recognition [24]. In addition, VGG16 is also applied to the ECG beat classification task to identify arrhythmias [2].

2.3 Adam optimizer

The Adam optimization algorithm [26] is an extension to stochastic gradient descent in updating network weights during the training process. It was introduced in the 2015 ICLR paper entitled "Adam: A Method for Stochastic Optimization" by Diederik Kingma and Jimmy Ba. The name Adam stands for adaptive moment estimation. The algorithm of Adam has attractive properties when it is used for non-convex optimization problems, such as: easy to implement, computationally efficient, low-space memory required, invariant to diagonal rescale of the gradients, effectively applicable for large dataset, appropriate for non-stationary objectives and very noisy or sparse problems, and suitable for hyper-parameters with intuitive interpretation and typically require little tuning.

The algorithm performs well on online and non-stationary problems (e.g. noisy). To maintain the per-parameter learning rate, Adam combines the advantages of two extensions of stochastic gradient descent, including:

1. Adaptive Gradient Algorithm (AdaGrad) to improve the performance on problems with sparse gradients, and
2. Root Mean Square Propagation (RMSProp) that adapts the learning rate based on the average of recent magnitudes of the gradients for the weight.

Adam configuration parameters include:

- **alpha** (learning rate or step size): The proportion to update the neuron weights. Regularly, this is set to 0.001. The larger the value, the faster the learning process, while the smaller value slows down the learning process.
- **beta1**: The exponential decay rate for the first moment estimates.
- **beta2**: The exponential decay rate for the second-moment estimates. For the problem with a sparse gradient, this value should be set close to 1.0.
- **epsilon**: A very small number to prevent division by zero in the implementation.

To date, Adam optimizer has become the reference for every study that trains deep neural network models and proves the superiority of the algorithm [27]- [30].

3 Results and discussion

This section discusses the performance of the proposed system that has been simulated. The system runs on Google Colab-Pro with NVIDIA Tesla P100-PCIE GPU and 16 GB of RAM. A total of 291 images consisting of NSR, PVC and Bigeminy were simulated at this testing stage.

The test is carried out using two scenarios: the first scenario, the image is not augmented and the second scenario, the image is augmented to increase the number of images. The purpose of the second scenario is to test the robustness of the proposed system model. The other scenario is to test the system in two classes and three classes. Two-class classification cases involved normal ECG (NSR) and abnormal ECG (PVC and Bigeminy). Meanwhile, the three classes are classified as normal, PVC, and Bigeminy. For classification, two classes consist of NSR with 103 images and abnormal (PVC and Bigeminy) with 188 images. For classification, three classes consist of NSR with 103 images, PVC with 133 images, and Bigeminy with 55 images. Meanwhile, the augmented scenario includes NSR with 238 images and abnormal (PVC and Bigeminy) with 330 images. For scenario three classes consist of NSR with 238 images, PVC with 133 images, and Bigeminy with 197 images.

To avoid overfitting, several parameters were added including a learning rate of 0.01, with 755 decay steps, 0.9 decay rate and using Adam's optimization optimizers. Furthermore, for the training process using batch size 32 with 20 epochs.

3.1 Convolution results as a discrimination feature

One of the stages in CNN is convolution which can be considered as a characterization process. This process occurs at the convolution layer. Figures 3, 4, and 5 below show the convolution results of black and white images representing NSR, PVC, and Bigeminy. Visually, the results of this convolution show that the ECG images have different patterns from each other so that the proposed ECG signal classification method based on the image is thought to generate high accuracy.

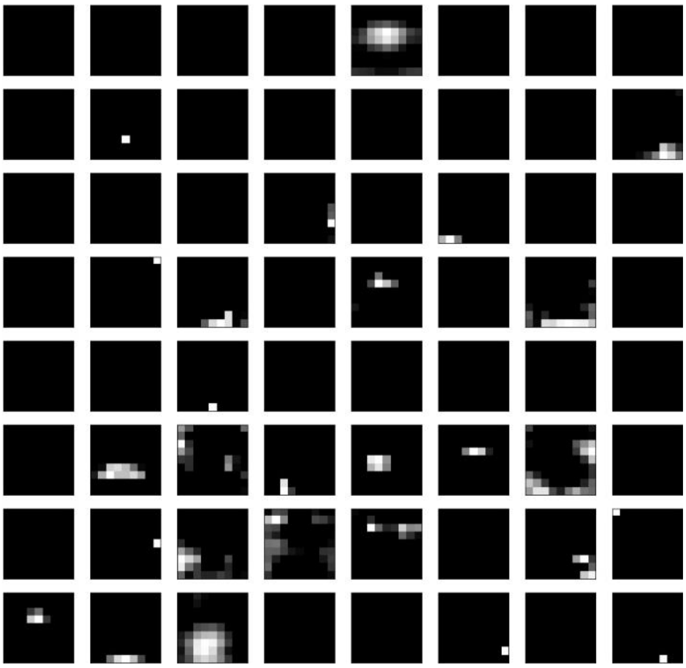


Fig. 3. Convolutional results in block-5 for NSR

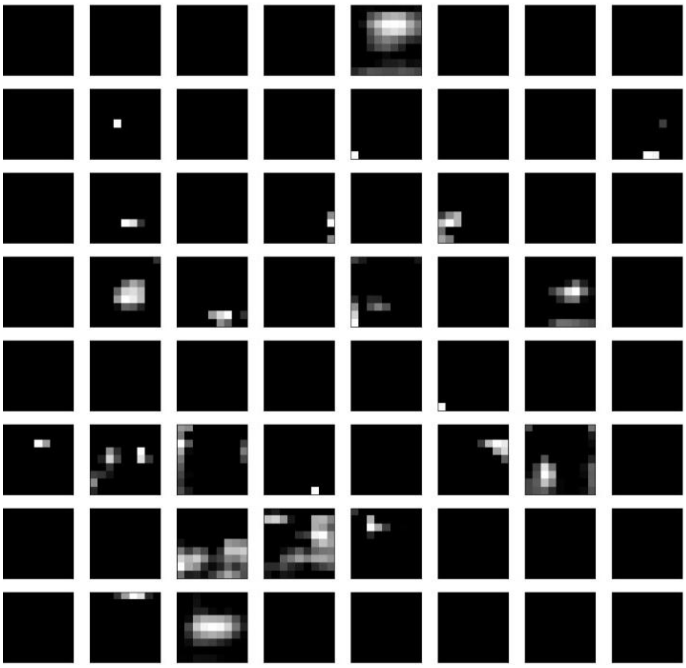


Fig. 4. Convolutional results in block-5 for PVC

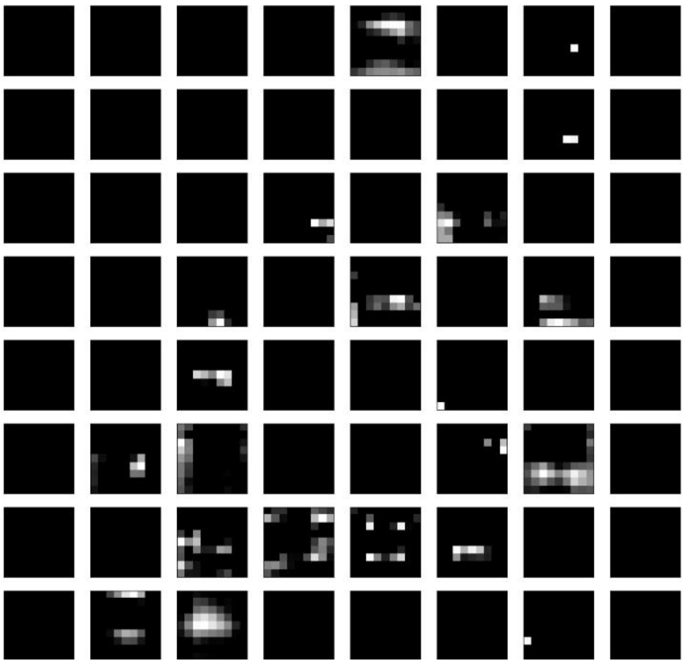


Fig. 5. Convolutional results in block-5 for Bigeminy

3.2 Analysis of the training and validation process on accuracy

Figures 6, 7, 8, and 9 show graphs of the results of the training and validation processes for two and three classes of classification scenarios. Also includes test scenarios with and without augmentation. It can be seen from the graph of the training results of each class with the methods that have been applied, it is concluded that using data augmentation can affect the accuracy results in the training process. It can be seen that the average training accuracy and validation accuracy are more stable than the scenario without augmentation. This indicates that the proposed system's performance becomes more robust in handling more data where there is no decrease in performance compared to the scenario without augmentation.

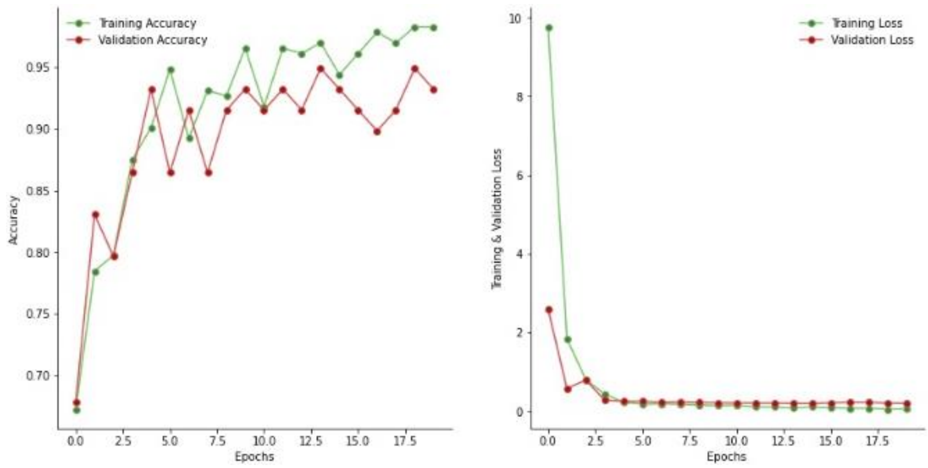


Fig. 6. Two-class training process without augmentation

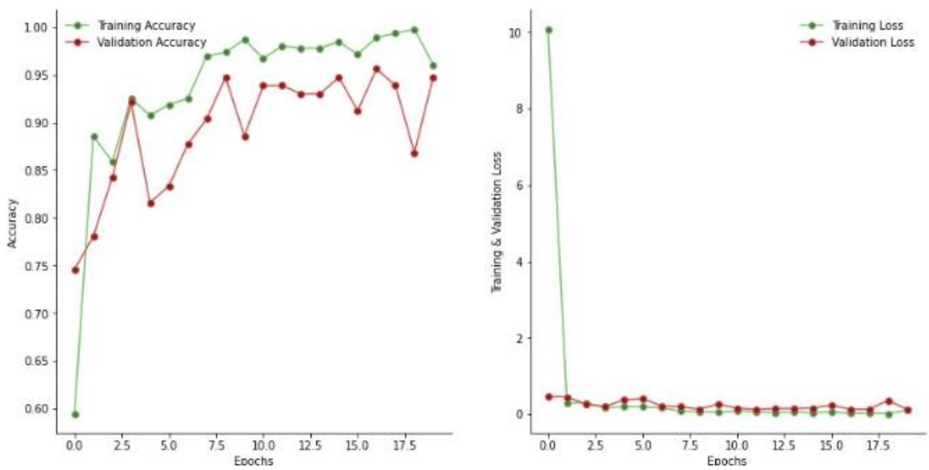


Fig. 7. Two-class training process with augmentation

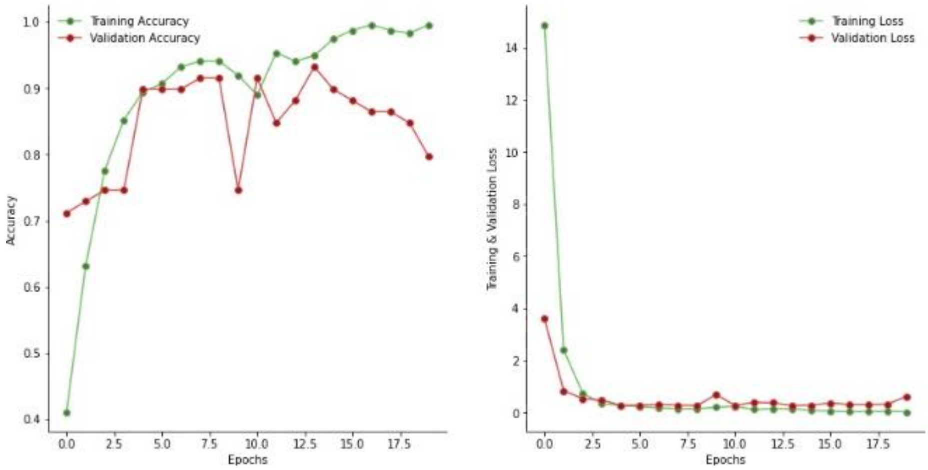


Fig. 8. Three-class training process without augmentation

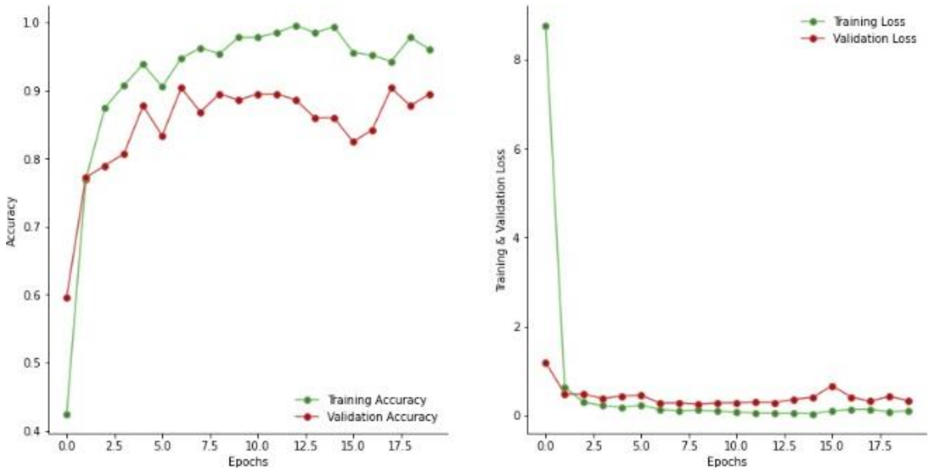


Fig. 9. Three-class training process with augmentation

3.3 Performance of proposed system in classification stage

This sub-section describes the results of testing each scenario using the VGG16 architecture with a transfer learning system. Tables 2, 3, 4, and 5 contain the values of precision, recall, and f1-score of the two-class and three-class test scenarios, both using and without augmentation.

From the test results as presented in Table 3 for the two-class classification scenario using augmentation, the highest precision was obtained at 98% with a recall value of 90% and an f1-score value of 94% for NSR. This result is relatively higher than without augmentation as presented in Table 2.

The average values of precision, recall, f1-score and accuracy are presented in Table 6. In the test scenario of two data classes using augmentation, 95% accuracy was obtained. Meanwhile, in the test scenario of three classes of data with augmentation, the accuracy is 89%. These results show better performance than without augmentation for both the two-class classification and the three-class classification. Another inference is that the proposed system is capable of detecting ECG abnormalities with up to 95% accuracy with the confusion matrix as presented in Figure 10.

From the test scenario of two classes and three classes of images, with augmentation will provide better performance than without augmentation. This could be because CNN requires more training data so that the characterization becomes more divergent for each class. In the case of PVC classification, it generates the lowest accuracy where there are many misclassifications as Bigeminy. This can happen because PVC and Bigeminy have a similar signal shape, besides that Bigeminy is a type of PVC. This study also shows that the proposed system is reliable in detecting ECG signal abnormalities based on signal images, furthermore the system is also capable of classifying PVC and Bigeminy with high accuracy. With this proposed system, it is hoped that it will simplify and assist clinicians in diagnosing ECG abnormalities.

Table 2. Precision, recall, F1-score on two class classification without augmentation

Class	Precision	Recall	F1-score
Normal (NSR)	0.91	0.91	0.91
Abnormal (PVC and Bigeminy)	0.95	0.95	0.95

Table 3. Precision, recall, F1-score on two-class classification with augmentation

Class	Precision	Recall	F1-score
Normal (NSR)	0.98	0.90	0.94
Abnormal (PVC and Bigeminy)	0.93	0.98	0.96

Table 4. Precision, recall, F1-score on three class classification without augmentation

Class	Precision	Recall	F1-score
NSR	0.92	0.96	0.94
PVC	0.94	0.58	0.71
Bigeminy	0.50	1.00	0.67

Table 5. Precision, recall, F1-score on three class classification with augmentation

Class	Precision	Recall	F1-score
NSR	0.92	0.92	0.92
PVC	0.81	0.93	0.86
Bigeminy	0.94	0.84	0.89

Table 6. The average of precision, recall, F1-score and accuracy

Classification scenario	Precision	Recall	F1-score	Accuracy
with augmentation				
2 Class	0.95	0.94	0.95	0.95
3 Class	0.89	0.90	0.89	0.89
without augmentation				
2 Class	0.93	0.93	0.93	0.93
3 Class	0.79	0.85	0.77	0.80

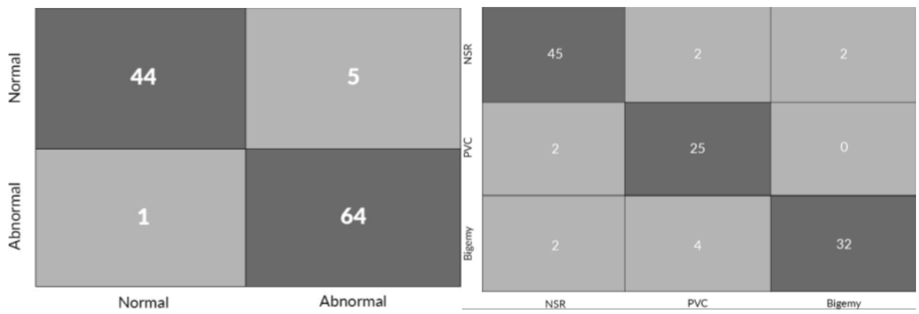


Fig. 10. Confusion matrix of highest accuracy

4 Conclusion

In this study, a CNN architecture has been proposed for the classification of ECG signals. Uniquely, in this study, the classification is not based on time series data but based on images of ECG signal. The basic CNN architecture used in this study is VGG16 with the Adam optimizer. The performance test scenario of the proposed system includes a two-class classification (normal vs abnormal ECG) and a three-class classification (normal vs PVC vs Bigeminy). Data augmentation was also carried out to test the robustness of the proposed method in classification on a larger dataset with balanced data between classes. The simulation results show that the proposed system is able to generate the highest accuracy of 95% for normal vs abnormal classification cases and 89% accuracy for normal vs PVC vs Bigeminy classification cases. This study can be an alternative in the analysis and classification of ECG signals using signal graphs or ECG signal images in addition to signal processing in the time domain. The image-based signal analysis approach can also tackle the problem of limited access to raw data on some ECG devices. There are still opportunities for future research to improve accuracy by modifying the CNN architecture or optimizing parameters in the training process. Another opportunity is the application of the system to a more varied type of ECG signal.dataset.

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