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Conference Paper

Arrhythmia Classification Using the Deep Learning Visual Geometry Group (VGG) Model

Rudolf Bob Martua B.[1]*, Alhadi Bustamam[1], Hermawan[2]

[1]Department of Mathematics, Universitas Indonesia
[2]Department of Cardiology, Rumah Sakit Universitas Indonesia

*Corresponding author:
E-mail:
rudolf.bob@sci.ui.ac.id

ABSTRACT

Cardiovascular disease (CVD) is one of the non-communicable diseases (NCDs) and 32% of the world's people die prematurely due to cardiovascular disease (WHO, 2022). The development of computing technology and artificial intelligence (AI), especially Deep Learning (DL), has contributed significantly to helping medical personnel carry out initial pre-diagnosis and classification of heart disease. In this study, we limit heart rhythm detection research into two categories, namely, Normal (N) and Abnormal (An) which are visualized in a standardized amplitude vs time diagram on the PTBDB dataset. The classification model in this research uses the 1-dimensional Deep Neural Network (1D-DNN) Visual Geometry Group, namely, VGG11, VGG13, VGG16, and VGG19. The denoising technique presented in this study on each ECG data sample thereby improving the quality of training data for the AI detection model. The performance of the VGG16 model shows the best training and validation accuracy with the lowest loss, which is 97.85% accuracy; 97.99% precision; 99.75% recall; and 98.52% f1-score. In this way, medical personnel will be helped more quickly in efforts to prevent and control heart disease that occurs in society, especially in the lower middle class. Further research needs to be done to use VGG with more blocks if the structure of the dataset to be classified is much more complex.

Keywords: Arrhythmia, classification, 1D-DNN visual geometry group, signal denoising and accuracy

Introduction

Cardiovascular diseases (CVD) are a type of non-communicable disease (NCD) and are the leading cause of premature death worldwide. According to the World Health Organization (WHO), in 2019, approximately 17.9 million people, which is equivalent to 32% of the global population, died from cardiovascular disease. Of this number, around 85% were affected by heart disease and stroke, and 30% of deaths occurred in people under the age of 70. This trend is also reflected in Indonesia, where heart disease is the leading cause of death among the productive age group every year (World Health Organization, 2022). Heart abnormalities can come from various factors such as congenital, hereditary heart structure abnormalities, or can also be due to an unhealthy lifestyle such as diet, smoking, or inaccuracy in doing heavy work or exercise (Rossignol et al., 2019). Based on the damage or abnormality experienced and the cause, heart disease is grouped into several types, namely coronary heart disease, congenital heart disease, arrhythmia, and endocarditis. Early detection of heart abnormalities can be performed by checking the condition of the heart with tools such as an electrocardiogram (ECG).

Along with the development of computing technology in carrying out the task of classifying disease symptoms, the role of artificial intelligence (AI), especially Deep Learning (DL) or Machine Learning (ML), has contributed significantly to big data which continues to increase in real-time

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and in complexity in the health sector. The presence of AI, especially through DL or ML algorithms, will help medical personnel to pre-diagnose the symptoms of a disease, including cardiovascular diseases such as heart disease (Li et al., 2022).

Electrocardiogram is a technique in the world of medicine, especially in the heart, which uses an electrocardiogram machine to record changes in the heart's electrical activity while the heart is in the circulatory cycle phase of circulating red blood cells throughout the body (World Health Organization, 2022). ECG is a tool consisting of 12 leads that can record heart activity by placing several electrodes in the thorax area. This recording will produce an image of the heart activity that occurs so that it can also record any abnormalities in the form of ECG graph paper. Proper classification of the disease allows for more focused treatment (Hernandez-Matamoros et al., 2020).

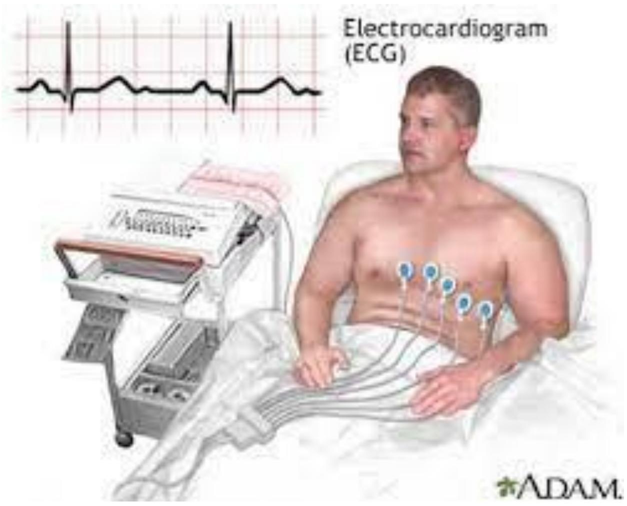

Figure 1. An electrocardiogram machine provides information on how fast the heart beats, whether there is a normal or abnormal heart rhythm pattern, how strong the amplitude of the heart rhythm is, and the timing of electrical signals that occur during the blood circulation cycle in the body

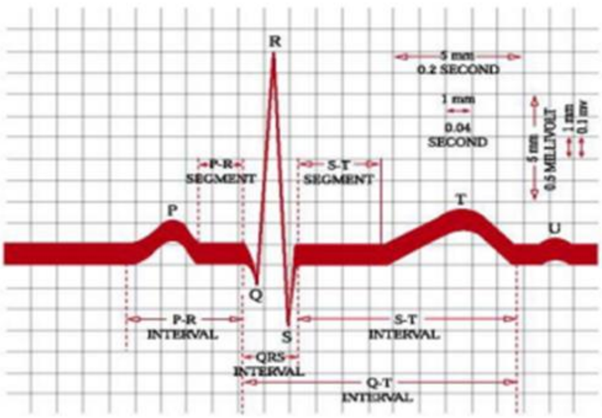

Figure 2. Example of a normal ECG (Jankowska-Polańska et al., 2022)

Based on information from the World Health Organization (WHO), several people in the world die every year accompanied by symptoms of arrhythmia (daviddalpiaz.github.io., 2022). Symptoms of arrhythmia are an abnormal pattern of electrical impulses to the myocardium, such as the heart beating too fast or too slow so that the heart's work in pumping blood does not work effectively and can cause death. In a healthy heart, arrhythmia conditions still often occur. However, if it occurs continuously, it can indicate a problem with the heart organ. Symptoms of arrhythmia can include dizziness, fatigue, or chest pain. However, arrhythmia can also occur without any symptoms, so the sufferer is not aware of it (Jankowska-Polańska et al., 2022). Judging from the signal, arrhythmia can be seen from abnormal heart rate (HR) per minute over a long recording duration.

In this study, we limited heart rhythm detection research into two categories, namely normal (N) and abnormal (A). Therefore, heart rhythm detection is important in carrying out initial prediagnosis in carrying out appropriate medical action in the subsequent process.

Material and Methods

This chapter presents the PTB ECG Signal Datasets, including a preprocessing dataset and several proposed methods of Visual Geometry Group (VGG). The research plan flowchart is shown in Figure 3.

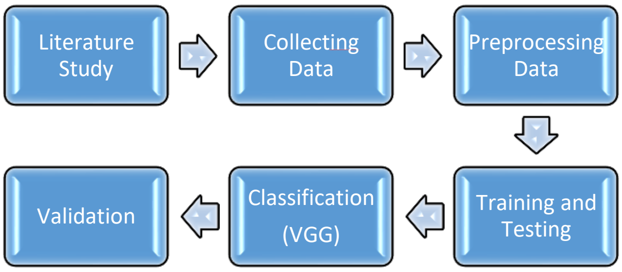

Figure 3. The flowchart research plan

PTB ECG signal dataset

Physikalisch-Technische Bundesanstalt (PTB) signal dataset, the National Metrology Institute of Germany, has provided this compilation of digitized ECGs for research, algorithmic benchmarking, or teaching purposes to the users of Physio Net. The database contains 549 records from 290 subjects (aged 17 to 87, mean 57.2; 209 men, mean age 55.5, and 81 women, mean age 61.6; ages were not recorded for 1 female and 14 male subjects). Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals: the conventional 12 leads together with the 3 Frank lead ECGs (Bjor, 2019; Bousseljot et al., 2009; Goldberger et al., 2020).

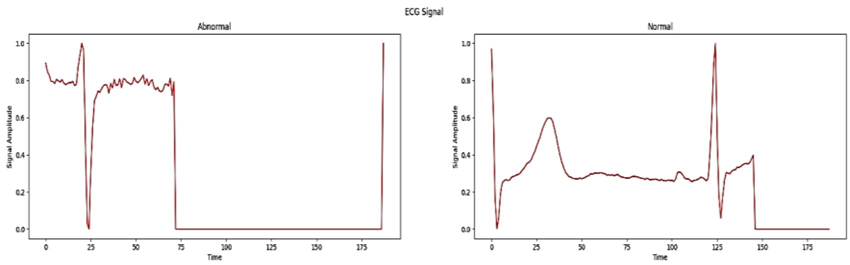

Figure 4. Normal (N) and Abnormal (An) heartbeat rhythm types are visualized in a standardized amplitude vs time diagram on the PTBDB dataset (Bjor, 2019; Bousseljot et al., 2009; Goldberger et al., 2020).

Visual Geometry Group (VGG) blocks

The idea of using blocks first emerged from the Visual Geometry Group (VGG) at Oxford University, in their eponymously-named VGG network. It is easy to implement these repeated structures in code with any modern deep-learning framework by using loops and subroutines

(Zhang et al., 2023). The basic building block of CNNs is a sequence of the following (Mathworks, 2023):

(i) a convolutional layer with padding to maintain the resolution,
(ii) a nonlinearity such as a ReLU,
(iii) a pooling layer such as max pooling to reduce the resolution.

One of the problems with this approach is that the spatial resolution decreases quite rapidly. This imposes a hard limit of $log_2\ d$ convolutional layers on the network before all dimensions are used up. The key idea was to use multiple convolutions between down sampling via max-pooling in the form of a block. They were primarily interested in whether deep or wide networks perform better.

A VGG block consists of a sequence of convolutions with 3×3 kernels with padding of 1 (keeping height and width) followed by a 2×2 max-pooling layer with a stride of 2 (halving height and width after each block). We define a function called vgg_block to implement one VGG block. The function below takes two arguments, corresponding to the number of convolutional layers number of convolutions, and the number of output channels number of channels (Zhang et al., 2023).

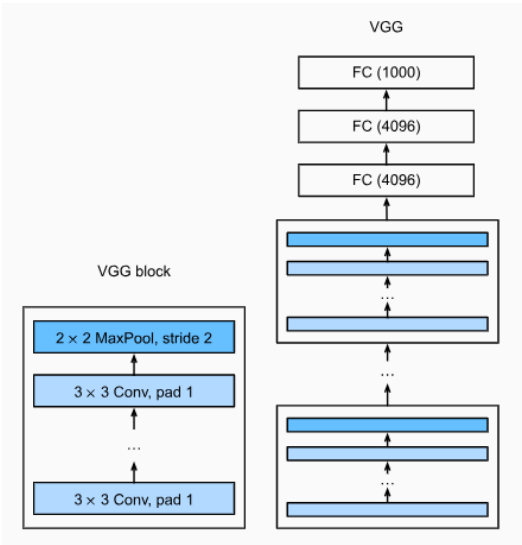

Figure 5. The architecture of VGG Blocks

VGG network

The original VGG network had five convolutional blocks, among which the first two have one convolutional layer each and the latter three contain two convolutional layers each. The first block has 64 output channels and each subsequent block doubles the number of output channels until that number reaches 512. Since this network uses eight convolutional layers and three fully connected layers, it is often called VGG-11.

The similarities in the structure of VGG11, VGG13, VGG16, and VGG19 lie in the convolutional layer, max-pooling, and fully connected layer. Meanwhile, the difference lies in the number of convolution blocks. VGG11, VGG13, VGG16, and VGG19 have several convolutional blocks of 8, 10, 13, and 16 respectively. VGG16 (also called Oxford Net) is a convolutional neural network architecture named after the Visual Geometry Group from Oxford, which developed it. It was used to win the ILSVR (ImageNet) competition in 2014. The key difference is that the convolutional layers are grouped in nonlinear transformations that leave the unchanged dimension, followed by a resolution-reduction step (Zhang et al., 2023).

Comparative analysis

The following table also offers a chronological summary of three performance metrics: Accuracy (Acc), Sensitivity (Se), and Specificity (Sp) for each DL classifier.

Table 1. Deep learning classifier

Manual Counting (actual) / Machine Learning (predicted)	**True (1)**	**False (0)**
True (1)	**True Positive (TP)**	**False Positive (FP)**
False (0)	**False Negative (FN)**	**True Negative (TN)**

FPR (False Positive Rate) represents the proportion of healthy patients wrongly identified as sick. FNR (False Negative Rate) represents the proportion of sick patients wrongly identified as healthy. Sensitivity (True Positive Rate) represents the proportion of sick patients who are correctly identified as such. Sensitivity (Se), or the True Positive Rate (TPR), is the proportion of actual positives (arrhythmias) correctly recognized by the model. It is critical in medical diagnostics since high sensitivity suggests that the model can reliably detect arrhythmias, lowering the possibility of false negatives.

Equations:

False Positive Rate $= \frac{FP}{FP+TN}$ ....(1)

False Negative Rate $= \frac{FN}{FN+TP}$ ....(2)

Sensitivity = True Positive Rate $= \frac{TP}{TP+FN}$ ....(3)

Specificity = True Negative Rate $= \frac{TN}{TN+FP}$ ....(4)

Youden index $= Sensitivity + Specificity - 1$ ....(5)

Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$ ....(6)

A model with inadequate sensitivity may fail to detect critical abnormalities, potentially resulting in serious health consequences.

Specificity (True Negative Rate) represents the proportion of healthy patients correctly identified as such. Specificity (Sp), also known as the True Negative Rate (TNR), is the proportion of real negatives (no arrhythmias) that are accurately detected. In essence, it indicates the model's ability to prevent incorrect diagnosis. This property is significant because a poor specificity model may result in unnecessary treatments or tests due to many false positives. This metric is important when gauging the overall reliability of a model.

Youden index is a measure of how well a diagnostic test can distinguish between sick and healthy patients. Accuracy represents the proportion of correct diagnoses among all patients, whether sick or healthy.

Accuracy (Acc) is an essential performance measure in classification problems. It assesses a model's overall accuracy by computing the proportion of total predictions the model correctly predicted, including positives (arrhythmia) and negatives (no arrhythmia). While accuracy gives a rapid overview of how well a model performs, it does not provide precise details about how well it performs on particular classes, which is especially important when the dataset is imbalanced.

Taken together, these three metrics: accuracy, sensitivity, and specificity, provide a more holistic and nuanced view of the performance of a DL model in the context of ECG arrhythmia detection and classification. They provide a balanced evaluation that accounts for overall performance and the accuracy of class identification, ensuring that the model performs well across all categories and does not overlook any one category.

Propose preprocessing method

In the proposed preprocessing method, two features are used: slicing and smoothing. The slicing feature captures the P-Q-R-S-T wave pattern, while the smoothing feature reduces the noise of the ECG PTB signal datasets.

Moving average filter

The moving average is the most common filter in digital signal processing (DSP), mainly because it is the easiest digital filter to understand and use. Despite its simplicity, the moving average filter is optimal for a common task: reducing random noise while retaining a sharp step response. This makes it the premier filter for time-domain-encoded signals. As the name implies, the moving average filter operates by averaging a set of points from the input signal to produce each point in the output signal. In equation form, this is written:

$$y[i] = \frac{1}{M}\sum_{j=0}^{M-1} x[i+j] \quad (7)$$

In this equation, $x[\ ]$ is the input signal, $y[\ ]$ is the output signal, and M is the number of points used in the moving average. This equation only uses points on one side of the output sample being calculated. A moving average filter smooths data by replacing each data point with the average of the neighboring data points defined within the span.

The moving average smoothing method used by the Curve Fitting Toolbox follows these rules:

- The span must be odd.
- The data point to be smoothed must be at the center of the span.
- The span is adjusted for data points that cannot accommodate the specified number of neighbors on either side.
- The endpoints are not smooth because a span cannot be defined.

Note that the filter function can be used to implement different equations such as the one shown above. However, because of the way that the endpoints are treated, the toolbox moving average result will differ from the result returned by the filter.

The differences between original signals (Normal and Abnormal) and smoothed signals are shown in Figure 6.

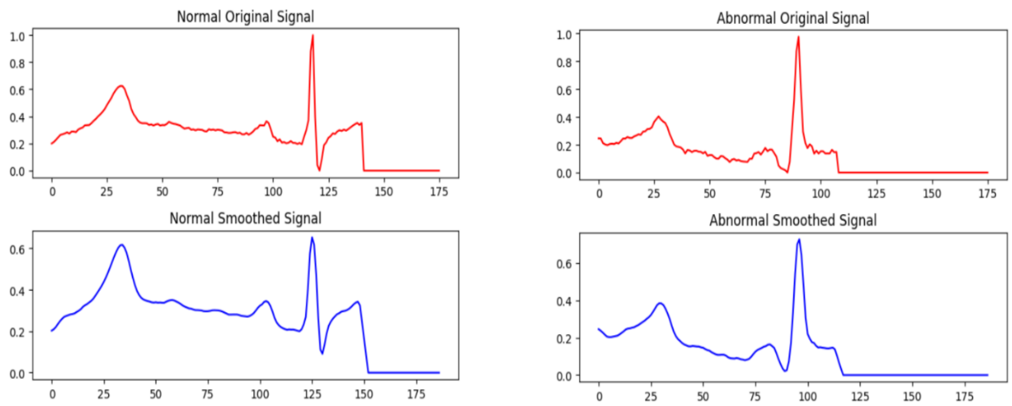

Figure 6. Original signals and smoothed signals (Normal and Abnormal)

Results and Discussion

Preprocessing ECG signal datasets

In the original ECG signal datasets, there are 10,506 rows x 187 columns for Abnormal data and 4046 rows x 187 columns for Normal data. Figure 4 shows that in the data there are noise/outliers that need to be carried out by denoising techniques which are expected to have the impact of increasing accuracy results in classifying arrhythmias. The cutting technique is carried out for each existing data, namely cutting 6 columns on the left and right of the data to remove extreme peak waves so that the data collected later can reduce existing noise/outliers as shown in Figure 7.

Next, a mean filter technique is carried out for each dataset to produce a smoother image (smoothing technique) as shown in Figure 6. As explained above, this can reduce random noise while retaining a sharp step response. It is important to note that the synthesized electrocardiogram (ECG) signals displayed noticeable noise. The origin of this noise can be attributed to inherent flaws present in the original ECG dataset, such as truncations and irregular waveform patterns. Finally, resizing was carried out by adding columns and grouping the data based on Normal (0) and Abnormal (1) at the end of the column, namely column 188. After going through the denoising technique, there were 8404 data trains for Abnormal and 3236 data trains for Normal with a total of 11,640 rows x 188 columns.

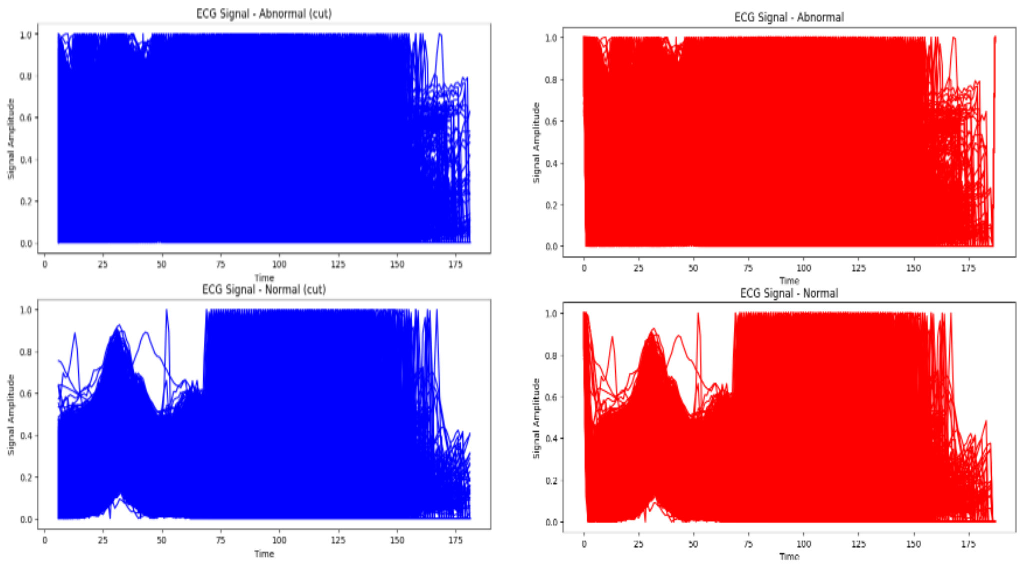

Figure 7. ECG signal datasets after Cutting technic

1D-CNN classification model

To evaluate the effectiveness of the enhanced synthesized data, this study utilized a 1D-CNN as an experimental model. One of the key advantages of the one-dimensional convolutional neural network (1D-CNN) model comes from its ability to effectively determine the information found in one-dimensional data signals. The present model demonstrates proficiency in enhancing the extraction of structural information from single-dimensional vector datasets by applying its convolutional layers. After the application of the convolutional layers, batch normalization layers are utilized to improve the stability and effectiveness of the model. In the context of neural networks, Maximum Pooling layers are employed to decrease the dimensions of the data, thereby reducing the overall complexity of the data. The CNN architecture is characterized by its efficiency, which is evident through its low complexity, fast processing speed, and ability to achieve comparable results with fewer training samples when compared to other conventional neural network models.

The present model consists of a total sum of 22.694.226 parameters, each of which possesses the capacity for training. The architecture of the 1D-CNN model is characterized by its simplicity, consisting of three convolutional layers that are augmented with batch normalization and max pooling layers to reduce dimensionality. Additionally, the model includes two dense layers and employs a softmax activation function to assign data samples to their respective class probabilities. Consequently, this model may require reduced training durations and exhibit decreased memory usage. However, its ability to depict complex characteristics may be limited.

The hyperparameters used in the training procedure consist of batch size and epochs. The selection of a batch size of 128 is motivated by the observation that smaller batch sizes generally produce the regularization effect and lead to a reduction in generalization error. Computational efficiency is a notable characteristic of these methods, as they show faster convergence rates compared to using the complete dataset. In contrast, the epoch is designated as 25, suggesting the total number of iterations through the training dataset. An insufficient number of epochs may give rise to underfitting, whereas a large number of epochs can potentially result in overfitting. Consequently, following a series of experiments and considering the dataset's size and characteristics, it was determined that 25 epochs provided the most effective approach.

Figure 8 shows that the accuracy during the training and validation processes does not encounter any major difficulties. However, between the 1st and the 3rd epochs, underfitting occurred in the error rates for both training and validation. This underfitting indicates that the model may have been overly simple or the learning rate excessive, which prevented the model from accurately capturing the underlying trend of the data. This problem could be resolved by modifying the architecture or tuning other hyperparameters.

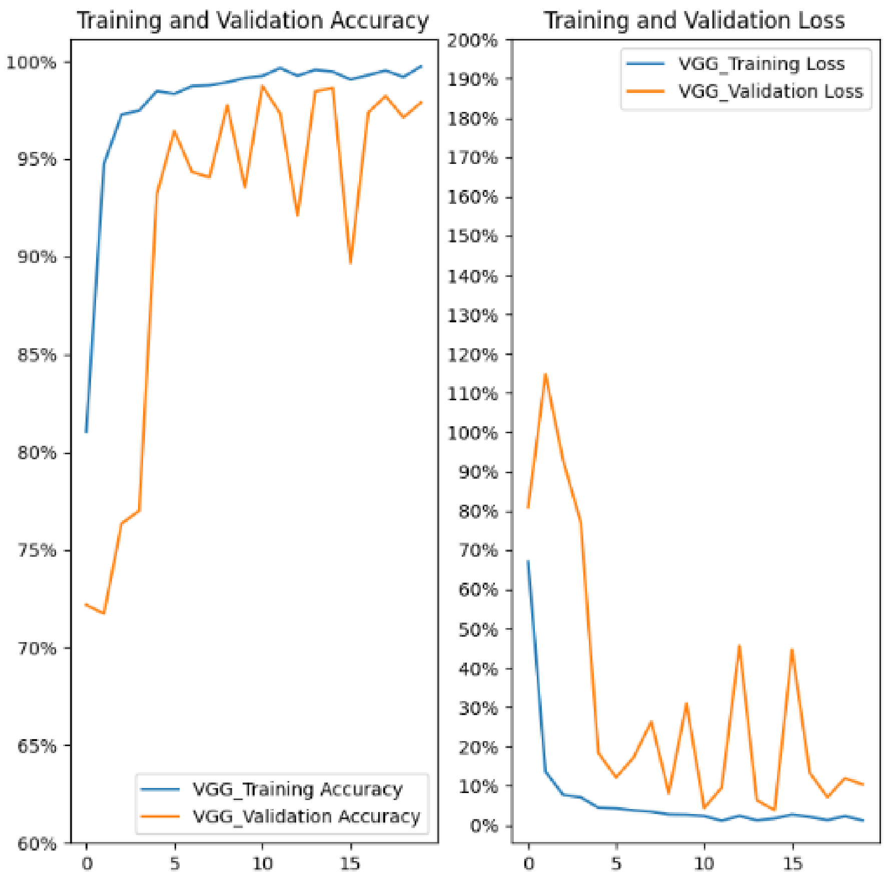

Figure 8. Accuracy and loss in training model

The confusion matrix, as shown in Figure 9, can be used to evaluate the effectiveness of the 1D-CNN. In this matrix, it is clear that the validation outcomes, derived from the weights estimated by the 1D-CNN model, demonstrate a high level of excellence. This observation is confirmed by the main diagonal, which extends from the top-left to the bottom-right and shows values of 99% and 97%. This indicates that work performance is quite good in direct proportion to the research.

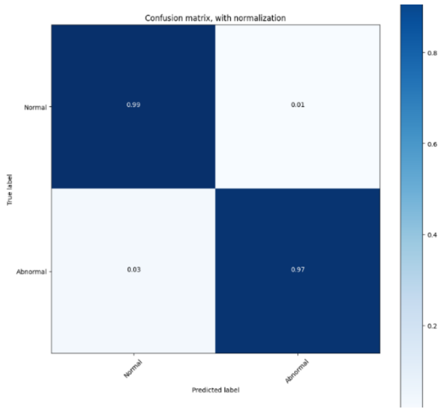

Figure 9. Matrix confusion for the 1D-CNN model classification

Visual Geometry Group (VGG) model

In previous research, biometric authentication speed increased with more stable results on the ECG-ID database set and the MIT-BIH Arrhythmia Database resulting in approximately 99% accuracy on both datasets. By using a less dense VGG block architecture network, the proposed method improves the classification accuracy more than the previously proposed scheme (Venkata et al., 2022).

Table 2. State of the art

Model	Previous Research	Aspect	Dataset (Object)	Performance
VGG	(Venkata et al.,2022)	This network utilizes a far simpler block architecture inspired by VGG architecture, and the less dense architecture improves speed.	ECG-ID and ECG Signal MIT-BIH	99% accuracy
CNN (AlexNet, ResNet-50, InceptionNet, and VGG-16)	(Nursalim et al., 2023)	classify 5 types of arrhythmia disorders from the MIT-BIH database	ECG Signal MIT-BIH	97.55% for VGG-16 accuracy
VGG	(Rajendra et al., 2022)	VGG architecture and the less dense architecture improve speed	ECG Signal MIT-BIH	94.03% and 93.47% for accuracy
VGG16, Inception V3, Alexnet	(Naz et al., 2021)	heuristic Entropy Calculation	ECG Signal MIT-BIH	97.60% for accuracy

Nursalim et al. (2023), and Atmadja et al. (2022) wrote that preprocessing techniques for smoothing ECG signals are important to increase the accuracy of deep learning models that use extraction features in convolution neural network architectures, including CNN models and VGG models. The results show that the accuracy value reached 97.55% for VGG16, while in Hendrico's research, it was said that the best way to determine the effectiveness of the 1D-CNN classification when used with GANs-Transformer reconstructed data is to use a confusion matrix. The performance was excellent because the diagonal representation of 100% indicates perfect class prediction. This perfection refers to precision, recall, and F1-Score that are at their best and underlie the model's accuracy in identifying positive cases without false negatives.

In his research, Rajendra developed a 9-layer deep convolutional neural network (CNN) to automatically identify 5 different heart rate categories in original and noise-attenuated ECG signals derived from publicly available databases. Artificially, the dataset was augmented to average the number of occurrences of 5 classes of heartbeats and filtered to remove high-frequency noise. The CNN was trained using additional data and resulted in accuracies of 94.03% and 93.47% in heart rate diagnostic classification. When the CNN is trained with highly imbalanced data (original dataset), the accuracy of the CNN reduces to 89.07%% and 89.3% on noisy and noise-free ECGs (Rajendra et al., 2017).

Meanwhile, Mahwish Naz proposed a new deep-learning approach to detect ventricular arrhythmias. Initially, ECG signals were converted into images that had never been done before. Then, the images are normalized and used to train the VGG-16 model via deep learning methods. Transfer learning is performed to train the model and extract deep features from different output layers. After that, the features are combined by a pooling approach, and the best feature is selected using a heuristic entropy calculation approach. Finally, a supervised learning classifier is used for final feature classification. The results were evaluated on the MIT-BIH dataset and an accuracy of 97.6% was achieved (using support vector machine cubic as the final stage classifier) (Naz et al., 2021).

Table 3. Comparison of model result

No	Model	Number of Parameters	Accuracy	Precision	Recall	f1_score
1	**VGG11**	Total params: 20585038 (78.53 MB) Trainable params: 20583740 (78.52 MB) Non-trainable params: 1298 (5.07 KB)	94.19%	93.96%	99.14%	96.29%
2	**VGG13**	Total params: 21316588 (81.32 MB) Trainable params: 21314976 (81.31 MB) Non-trainable params: 1612 (6.30 KB)	95.95%	95.36%	99.27%	97.27%
3	**VGG16**	Total params: 22694226 (86.57 MB) Trainable params: 22691346 (86.56 MB) Non-trainable params: 2880 (11.25 KB)	**97.85%**	**97.99%**	**99.75%**	**98.52%**
4	**VGG19**	Total params: 24311978 (92.74 MB) Trainable params: 24307494 (92.73 MB) Non-trainable params: 4484 (17.52 KB)	96.00%	95.42%	99.49%	97.35%

Arslan (2022) said that the focus of his research is to establish an efficient computer-aided diagnosis approach that detects HVD using phonocardiogram (PCG) signals. The proposed approach uses traditional time-frequency and deep features with machine learning models. Time-frequency features are extracted from nonlinear measurements using discrete wavelet transform (DWT), wavelet packet transform (WPT), perceptual wavelet packet transform (PWPT), and empirical mode decomposition (EMD) methods. Deep features are extracted from a pre-trained CNN model VGG16 and a multilayer extreme learning machine (ML-ELM) using a scalogram image of the PCG signal. The recursive feature elimination (RFE) algorithm is applied to all features and the most typical features are selected.

In this research, the VGG11, VGG13, VGG16, and VGG19 models each show different performances. The VGG-16 model is one of the models that provide promising results which is quoted from the research results of Rashed, et al which shows accuracy approaching 100% for the MIT-BIH dataset (Rashed-Al-Mahfuz, 2021) which is directly proportional to the results of this research which uses ECG signal datasets. Based on the results of this research, the data were obtained as shown in Table 3.

This research has initiated discussions with experts in the field of cardiology to validate the congruence between the synthesized results and the anticipated outcomes, particularly concerning the "normal" and "arrhythmia" categories. These categories will be the focus of future investigations. The synthesized results will be combined with the training dataset for the classification model of one-dimensional deep neural networks.

There are various methods and models used to classify arrhythmias using electrocardiogram signals. The model we proposed shows a linear correlation with previous researchers even though some hyperparameters have not reached the expected target.

Conclusion

The performance of the VGG16 model shows the best training and validation accuracy with the lowest loss, which is 97.85% accuracy; 97.99% precision; 99.75% recall; and 98.52% f1-score. Further research needs to be done to use VGG with more blocks if the structure of the dataset to be classified is much more complex.

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