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Improving Convolutional Neural Network with Recurrent Model and Generative Adversarial Networks for Imbalance Classification of Wearable ECG Signal Quality Assessment

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Abstract **Signal quality assessment is important procedure to assess if a signal can be preprocessed into next step or not. In this study, we proposed an improving of convolutional neural network with recurrent model and generative adversarial network. The experiment shows that enhancing convolutional neural network by using recurrent model or data augmentation via GAN for wearable ECG signal quality assessment is feasible to try. Adding recurrent model to CNN increase its performance by approximately 3% margin in un-augmented dataset. Generating fake samples from "unacceptable" class can enhance CNN performance up to 2% margin. Combination of recurrent model and GAN still not yet matched found. However, It doesn't mean that the combination is impossible to do.**

***Key words*: ECG, signal, quality assessment, convolutional neural network, recurrent model, generative adversarial networks.**

I. Introduction

Electrocardiography (ECG) is an important tool to monitor heart condition. The device is a mandatory sensor to detect hearth and cardiovascular diseases. During this vast development on biomedical devices, electrocardiography is no longer conducted only in hospital and health clinic, but also in a wearable device [1][2]. However, there are several important issues in wearable ECG signal analysis called false alarm. False alarm is a condition where an ecg signal is falsely analyzed that mostly caused by the noises within the signal. For example, a heart diseases class ecg signal is classified (predicted) as normal (health) signal, and a normal class is predicted as heart disease class. Therefore, assessing the quality of ecg signal captured from wearable sensor plays an important role in wearable signal analysis.

In ECG signal quality assessment, an ecg signal will be assessed if the signal is "acceptable" or "unacceptable" for further process [3]. There are several approaches that applied for ECG signal quality assessment. Shahriari et al proposed an ECG signal quality assessment using image similarity metric [4]. Kuzilek et al proposed an ECG signal quality assessment by using support vector machine (SVM) classifier [5]. Hermawan et al proposed ECG signal quality assessment using temporal feature and heuristic-based (rule-based) method [6]. Hermawan et al also measure the performance of the method compared with fully supervised classical machine learning method [7]. In summary, ECG signal quality assessment is conducted by using unsupervised approach, supervised approach and their combination.

According to the previous research, the performance of classical machine learning is not quite good. The methods achieved low specificity although they achieved high sensitivity. One of the main factors is its imbalance classes where the dataset of unacceptable class is less than the dataset of acceptable class with 1:3 to 1:4 ratio. In other side, we have advancement of deep learning methods that performs excellently in classification task. Variating the convolutional neural networks, fully connected layers and other mechanism produces a powerful deep neural network architecture called VGG, DenseNet, ResNet, and MobileNet [8-13]. Meanwhile, the advancement of deep learning also offers another approach to solve imbalance classification problem. Generative Adversarial Networks (GAN) and Variational Auto-Encoder (VAE) propose methods to generate fake (synthethic) data from real dataset by using trainable neural networks [14][15].

In this study, we proposed a convolutional neural network (CNN) for imbalance classification of wearable ECG signal. The main objective of using deep learning is because of its comprehensiveness where a network contains a feature extraction and classification unit. Then we tried to improve the performance of deep learning method by adding the recurrent model such as long short-term memory (LSTM) and gated recurrent unit (GRU) to improve the performance of the convolutional neural networks [16][17]. Then we also tried to improve the

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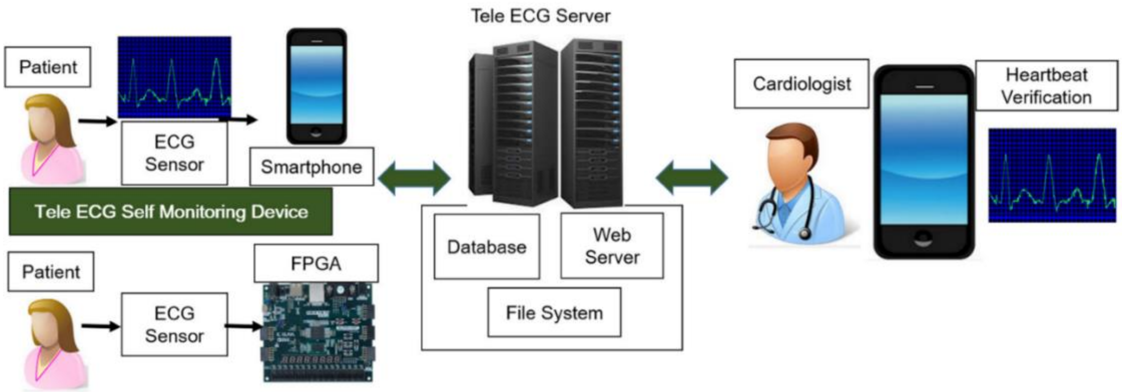

Fig. 1. Tele-ECG system with wearable ECG sensor [18]

performance of CNN by using data augmentation through generative adversarial networks. In summary, we proposed 2 contributions in this study. First, investigating the CNN performance and its enhancement by recurrent model for ECG signal quality assessment and proposing. an enhanced CNN with GAN for imbalance classification of ECG signal quality assessment.

The rest of the paper is organized as follows: section 2 discusses Tele-ECG system with wearable ECG sensor, section 3 discusses the proposed method, section 4 discusses experiment result and analysis, and the last section draws the conclusion of this study.

II. Overview Tele-ECG System

This study is the continuation of previous study in developing end-to-end Tele-ECG system for heart monitoring and early detection of hearth diseases as shown in Figure 1 [18][19]. Figure 1 shows that the Tele-ECG system consists of several components i.e., wearable ECG sensor, smartphone, or field programmable gate array (FPGA), and server. The system includes two actors i.e., patient and cardiologists. The first component is wearable ECG sensors that worn by the patient. The sensor is used to capture hearth signal from the patient. The second component is smartphone or FPGA. The device is used to visualize and analyzed the ECG signal digitally. The device is also able to predict the class label of the signal if it is a normal heartbeat or arrhythmia heartbeat. The third component is server. The server is deployed to connect the patient and the cardiologist via internet connection. The server also functions as storage of the recorded heartbeat signal. The server contains database, web server and file system.

In the previous study, the system utilized learning vector quantization (LVQ) based neural networks for ECG signal classification [20][21]. Different to this study, in previous study, the neural networks were trained by using 12-lead clean ECG signal. Therefore, the signal is guaranteed clean and can be classified. In this study, e attempt to add a predictor unit that can classify if the signal is “acceptable” or “unacceptable” for f=analysis. In this study we develop deep learning-based method for the ECG signal quality assessment.

III. Methodology

The illustration of the proposed method is shown in Figure 2. As mentioned before, the proposed method is combining convolutional neural network (CNN) and generative adversarial network (GAN). The CNN module is the main classifier for ECG signal quality assessment. The model is used to learn (train) the training dataset and then predict the testing dataset. During the training phase, the CNN model is getting help from the GAN model to enhance its performance. The GAN model is utilized ti produce fake samples dataset. The GAN module contains three models i.e., generator model, and discriminator model. The generator model is functioned to generate fake samples by learning to imitate real samples. While discriminator model tries to discriminate the real samples and fake samples by learning from the two of them. Besides, in this study, we applied a recurrent model to enhance the CNN. The CNN model is also enhanced by using recurrent model to learn in sequences order. Thus, the information between a state is used in the next state. This approach enhances the CNN model performance. More detailed information about each network is described in the following sub-sections.

A. Convolutional Neural Network (CNN) -1D

In this study we utilized 1-dimensional convolutional neural networks (1D-CNN). The CNN is a simple model with 2 convolutional layers. The CNN takes (3600,1) dimensional data as input. The convolutional layers both has 32 filters, 5 kernel size and 1 padding. The convolutional layers are continued with max pooling layer. The pooling layer is continued with flatten and fully connected layers. The fully connected layers has 32, 32, and 2 neurons respectively. The last layer is activated by using SoftMax function to classify the ECG signal. The architecture of the CNN network utilized in this study is shown in Figure 3.

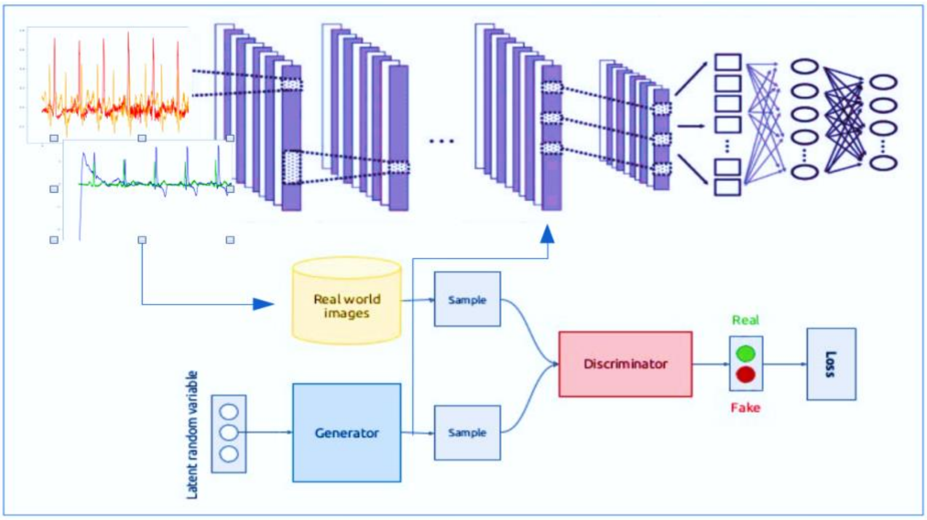

Fig. 2. Architecture of the proposed method

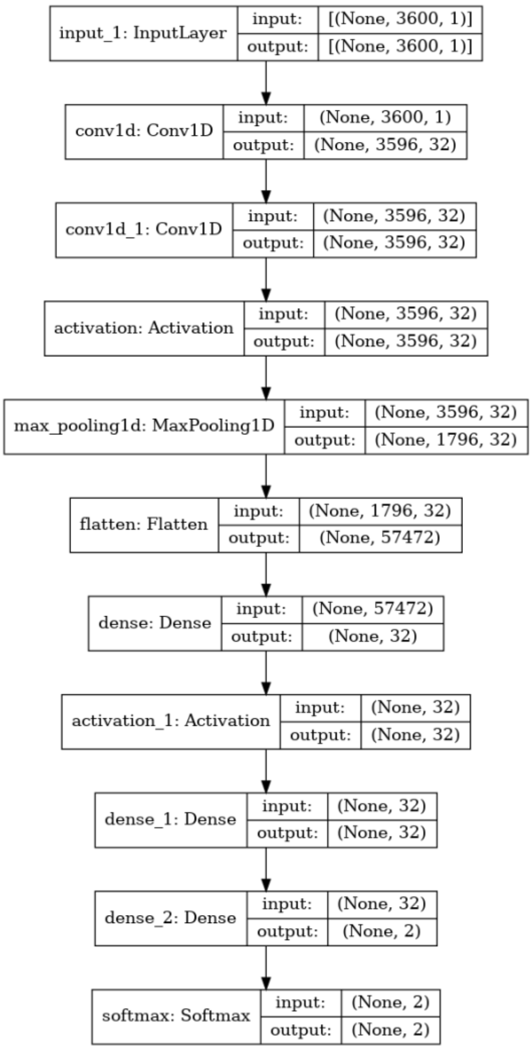

Fig. 3. Architecture of CNN

B. CNN-1D + Recurrent Model

As mentioned before, that in this study we try to enhance the CNN model with a recurrent model. We try to add LSTM and GRU model to the CNN model. Recurrent model is said to be able to memorize the information of the data train from previous iteration or batch. Therefore, recurrent model is suitable for time-series or sequence model. As we already know that ECG signal can be treated as time-series signal where a beat has similarities with other beats. In this study we investigated if the recurrent model can elevate the performance of CNN in ECG signal data.

The recurrent model is added as a layer in the CNN. The LSTM or GRU layer is applied after max pooling layer and before the flatten layer. The idea of adding recurrent layer is to memorize the featured of ECG signal from time to time. Therefore, the model can achieve a better performance. The example of CNN+Recurrent model is shown in Figure 4.

C. ResNet-1D

ResNet-1D is a one-dimensional deep neural network that built based on convolutional neural networks. In general, Resnet-1D has five blocks of CNN1D and one block of fully connected layer. One of the uniqueness of ResNet is skip connection and feature fusion. As shown in Figure 5, there is skipped connection from a max pooling layer of previous block to an activation layer of current block. This mechanism makes a feature fusion from current convolutional layer and previous max pooling layer. By using this mechanism, the model is able to merge two types of extracted features into operation. This mechanism generates another unique feature for the data. In this previous study, the skip connection and feature fusion is proven to be a strong contribution in image classification task.

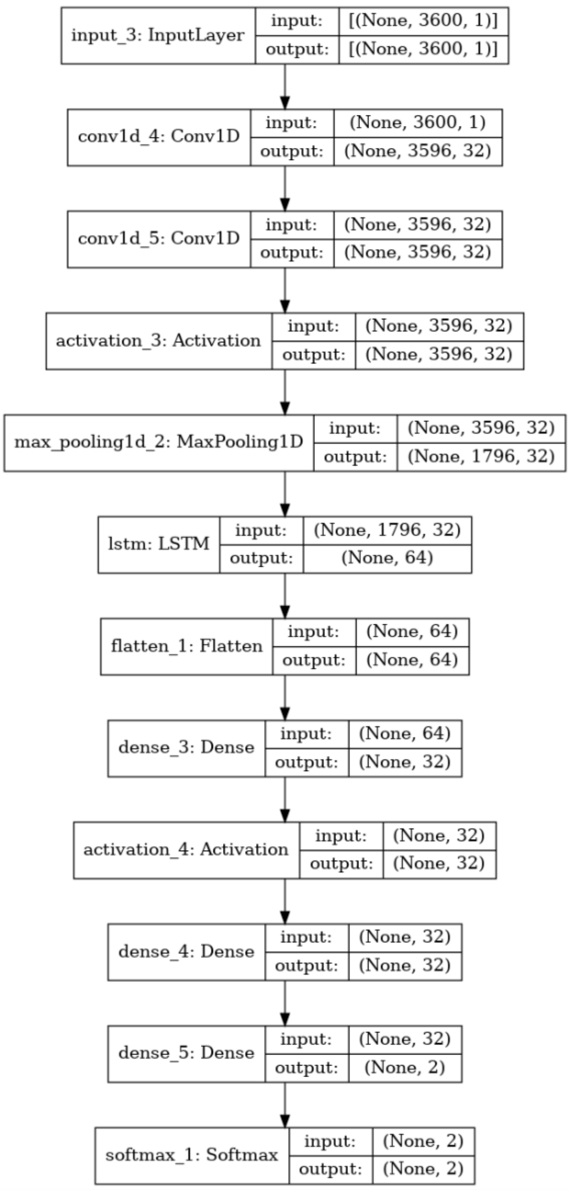

Fig. 4. Architecture of CNN+LSTM

D. Generator Model

Generator model is the model that is used for generating fake samples in GAN training mechanism. This model can convert a latent information into samples that like real samples. In this study we utilized fully connected layer as the generator model. The model consists of 3 layers of fully connected layer. The layer have 1024, 256 and 3600 neurons respectively. The generator model produces 3600 sized data that is the same size as input (real) data. The summary of the generator model is shown in Figure 6.

E. Discriminator Model

Generator model is the model that is functioned as the predictor to classify if a samples in GAN training phase is belong to fake or real sample.

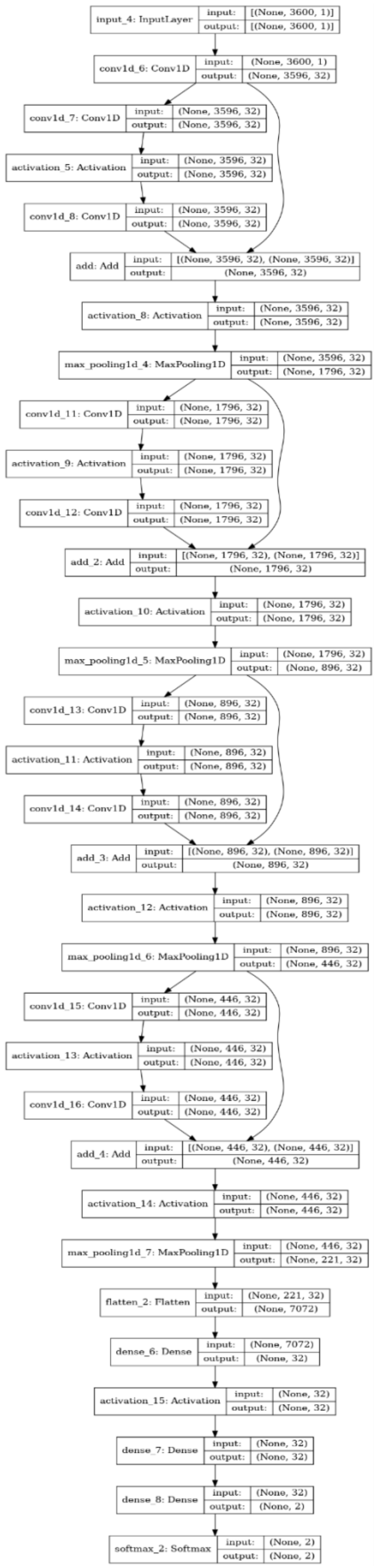

Fig. 5. Architecture of ResNet-1D

In line with the generator model, in this study we also utilize a fully connected networks as the discriminator model. The discriminator model has 4 layers of fully connected model. The layers have 1024, 256, 64 and 1 neurons respectively. The last layer denote that the discriminator network predicts the input data into one of the two class labels, i.e., "acceptable" and "unacceptable". The architecture of the discriminator model is shown in Figure 7. Both discriminator and generator model uses Leaky ReLU as the activation function of the layers.

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_24 (Dense)             (None, 1024)              3687424
_________________________________________________________________
leaky_re_lu_13 (LeakyReLU)   (None, 1024)              0
_________________________________________________________________
dense_25 (Dense)             (None, 256)               262400
_________________________________________________________________
leaky_re_lu_14 (LeakyReLU)   (None, 256)               0
_________________________________________________________________
dense_26 (Dense)             (None, 3600)              925200
=================================================================
Total params: 4,875,024
Trainable params: 4,875,024
Non-trainable params: 0
```

Fig. 6. Architecture of Generator Model

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 1024)              3687424
_________________________________________________________________
leaky_re_lu (LeakyReLU)      (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               262400
_________________________________________________________________
leaky_re_lu_1 (LeakyReLU)    (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                16448
_________________________________________________________________
leaky_re_lu_2 (LeakyReLU)    (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 65
=================================================================
Total params: 3,966,337
```

Fig. 7. Architecture of Discriminator Model

IV. Experiment Result And Analysis

This section discusses the dataset, experiment scenarios, the result and analysis of the scenarios.

A. Dataset

In this study we utilized the wearable ECG dataset from PhysioNet database. The dataset is part of Computing in Cardiology Challenge (CNC) 2011. In this study we use the lead 2 data as lead 2 ECG signal is widely used for Arrhythmias detection. The dataset consists of nearly 1000 instances (samples) where the ration between "acceptable" and "unacceptable" class is approximately 4:1. The example of the ECG signal quality assessment dataset is shown in Figure 8.

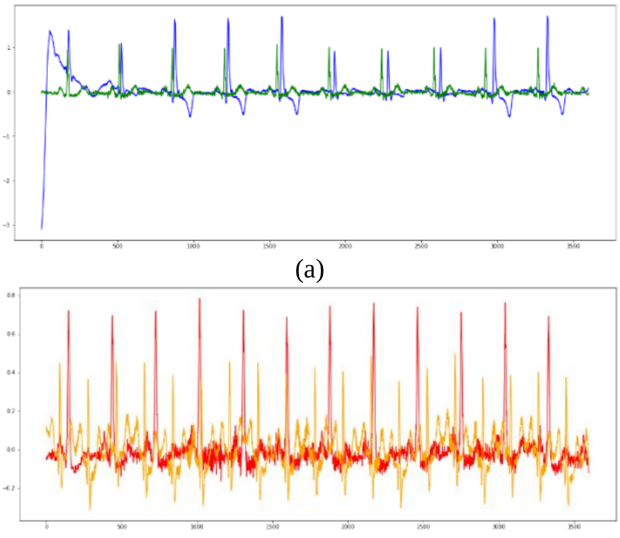

Fig. 8. Plot of ECG signal quality assessment dataset (a) acceptable class (b) unacceptable class

B. Experiment Setup and Scenario

In this study we designed three scenarios. The first scenario is conducted to measure if the addition of recurrent model enhances the CNN performance. The second scenarios is conducted to measure if the data augmentation via GAN can enhance the CNN and other models. Scenario three is conducted to measure performance of variation of data augmentations. In this study we measure the performance of the deep learning by using precision, recall, f1-score, accuracy, sensitivity, specificity and quality index. The formula of those metrics are written as below.

$$precision = \frac{TP}{TP + FP} \quad (1)$$

$$recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \quad (3)$$

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (4)$$

$$specificity = \frac{TN}{TN + FP} \quad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (6)$$

Quality index is defined as sqrt (sensitivity x specificity). Quality index concern about the ability to detect both class 0 and class 1. This metrics will be our main metrics to evaluate the model performance.

C. Result of Scenario 1: Improving CNN using Recurrent Model

In scenario, we measured the performance of the CNN and its enhanced version (CNN+recurrent model). In this study we proposed two variants of recurrent model i.e. LSTM and GRU. We also measured the performance of ResNet (1D version) as the representation of state of the art of deep learning architecture. The result of this scenario is shown in Figure 9 and 10. Figure 9 shows that the gap of training and testing accuracy of CNN and ResNet is far. Their training accuracy converges at 100% while their testing accuracy still on 80s % area. While the gap of training and testing accuracy of CNN+LSTM and CNN+GRU is narrower.

Figures 9 and 10 also show that the performance of CNN+LSTM and CNN+GRU is higher than the CNN only both from testing accuracy and testing loss. This result tells us two insights. First, the addition of recurrent model on CNN is increasing its performance. Two, the enhanced CNN with recurrent model tends to be more durable to local maxima and overfitting. Figures 9 and 10 show that the CNN and ResNet is most likely face overfitting condition as their training accuracy is nearly 100% but the testing accuracy stuck in 80% even we increase the epoch value.

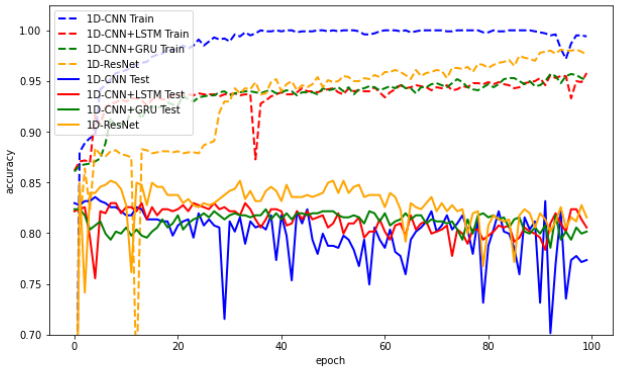

Fig. 9. Training and Testing Accuracy of CNN, CNN+Recurrent model, and ResNet

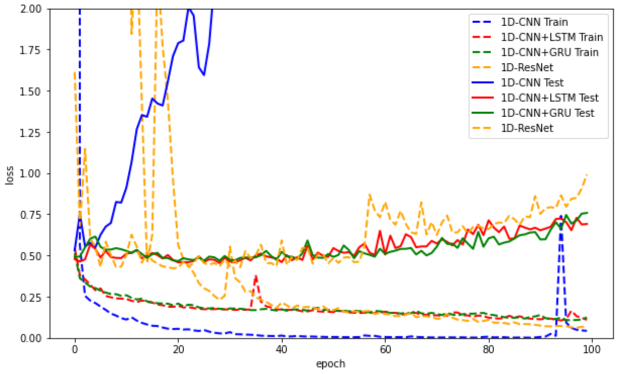

Fig. 10. Training and Testing Loss of CNN, CNN+Recurrent model, and ResNet

D. Result of Scenario 2: Improving CNN using Generative Adversarial Network

In this study we tried to measure the impact of data augmentation by GAN into the deep learning performance. In this scenario, we measure the performance of those four models with and without augmentation. In this scenario, we only augment the class 1 (unacceptable) since "unacceptable" class is the minority class in the dataset. Table I shows that the best performance in un-augmented dataset is achieved by CNN+SLTM with 83.354%, 71.996%, 75.367%, 85.371%, 96.623%, 47.368%, and 67.652% precision, recall, f1-score, accuracy, sensitivity, specificity, and quality index respectively. This result is followed ResNet and CNN with quality index more than 66% and 64% respectively. On the other side, CNN+GRU cat not perform well in this scenarios as shown in Table I with 59% quality index.

On the other case, in augmented dataset, the best performance is achieved by CNN with 77.572%, 70.386%, 72.681%, 82.164%, 93.617%, 47.154%a nd 66.441% precision, recall, f1-score, accuracy, sensitivity, specificity, and quality index respectively. Then it is followed by ResNet with more than 66 quality index. CNN+LSTM and CNN+GRU can not perform well in this case as shown by Table I that their quality index is less than 59%.

In summary, Table I shows that in augmented dataset, the performance of CNN is increasing approximately 2%. While the other models drop achieved lower performance in augmented data with 0.3-9% margin. Adding LSTM layer in un-augmented dataset increase CNN performance with approximately 3% margin.

E. Result of Scenario 3: Variation of Fake Samples

In this scenario, we tried to evaluate the model performance on several variation of fake samples source. After the generator and discriminator model were trained in GAN training mechanism, the fake samples can be generated by the generator. We have several option to generate fake samples i.e. using (randomized) latent feature or training data. The result of scenario 3 is shown in Table II.

Table II shows that in the case where we augment unacceptable class from its training set, the CNN and ResNet perform better than the others with more than 66% quality index. In the case where we augment unacceptable class from latent feature, the ResNet performs better than the others with more than 64% quality index. In the case where we augment unacceptable class from latent feature and its training set, the CNN and ResNet perform better than the others with more than 65% quality index.

TABLE I. RESULT OF SCENARIO 2: MODEL PERFORMANCE WITH VS WITHOUT AUGMENTATION

Data Augmentation	Model	Avg. Precision	Avg. Recall	Avg. F1-Score	Accuracy	Sensitivity	Specificity	Quality Index
No	CNN1D	71.987	68.44	69.809	80.361	90.39	46.491	64.825
	CNN1D+LSTM	83.354	71.996	75.367	85.371	96.623	47.368	**67.652**
	CNN1D+GRU	84.615	67.073	70.524	83.968	98.182	35.965	59.423
	Resnet1D	70.762	69.156	69.867	79.559	88.312	50.000	66.450
Yes	CNN1D	77.572	70.386	72.681	82.164	93.617	47.154	**66.441**
	CNN1D+LSTM	84.989	66.682	69.794	82.766	98.404	34.959	58.652
	CNN1D+GRU	84.546	65.869	68.804	82.365	98.404	33.333	57.272
	Resnet1D	72.428	69.204	70.455	79.559	89.628	48.780	66.122

TABLE II. RESULT OF SCENARIO 3: MODEL PERFORMANCE ON VARIATION OF AUGMENTATION DATA

Data Augmentation	Model	Avg. Precision	Avg. Recall	Avg. F1-Score	Accuracy	Sensitivity	Specificity	Quality Index
X_train[class1]	CNN1D	77.572	70.386	72.681	82.164	93.617	47.154	**66.441**
	CNN1D+LSTM	84.989	66.682	69.794	82.766	98.404	34.959	58.652
	CNN1D+GRU	84.546	65.869	68.804	82.365	98.404	33.333	57.272
	Resnet1D	72.428	69.204	70.455	79.559	89.628	48.78	**66.122**
Latent[class1]	CNN1D	70.871	66.898	68.284	78.557	89.894	43.902	62.821
	CNN1D+LSTM	75.18	64.547	66.684	79.96	94.947	34.146	56.939
	CNN1D+GRU	86.314	67.628	70.981	83.367	98.67	36.585	60.082
	Resnet1D	76.26	69.033	71.245	81.363	93.351	44.715	**64.608**
X_train[class1] +Latent[Class1]	CNN1D	75.682	69.174	71.25	81.162	92.819	45.528	**65.007**
	CNN1D+LSTM	80.826	66.017	68.752	81.764	97.074	34.959	58.255
	CNN1D+GRU	86.508	63.829	66.303	81.764	99.202	28.455	53.130
	Resnet1D	72.789	69.064	70.458	79.76	90.16	47.967	**65.762**
X_train[class1] +X_train[class0]	CNN1D	69.013	66.647	67.58	77.355	87.766	45.528	**63.212**
	CNN1D+LSTM	79.171	80.561	78.202	80.561	94.947	36.585	58.938
	CNN1D+GRU	77.031	63.585	65.7	80.16	96.277	30.894	54.538
	Resnet1D	80.082	65.884	68.548	81.563	96.809	34.959	58.175

In the case where we augment unacceptable and acceptable clasess from their training set, only the CNN performs better than the others with more than 63% quality index. Table II also shows that higher accuracy, f1-score, precision, and recall don't guarantee the higher quality index. The other insight is that using class 1 only augmentation from its training set, produces the highest performance of all variation, meanwhile combining augmentation from class 1 and class 0 lower the performance of the models.

F. Performance Comparison

After conducting those three scenarios, we compared the proposed method with the previous work by Hermawan et al. In the previous work, they utilize classical machine learning such as support vector machine (SVM), multi layer perceptron (MLP) and random forest classifier. From the current study, we take the best 3 models that achieved higher performance. In un-augmented dataset, CNNN+LSTM performs excellently with more than 96%, 47%, and 67% sensitivity, specificity and quality index respectively. The second-best performance is achieved by CNN in augmented dataset where the augmented data is generated from training dataset for class1 only. The method achieved more than 93%, 47%, and 66% sensitivity, specificity and quality index respectively\. The third place is achieved by ResNet with more than 89%, 46%, and 66% sensitivity, specificity and quality index respectively.

Compared to the previous research by Hermawan et al, current study achieved a better performance. In previous study, the RBF-SVM achieved 100%, 33%, and 57% sensitivity, specificity and quality index respectively. MLP achieved the same performance as RBF-SVM. Whereas random forest classifier achieves a slightly lower performance than RBF-SVM and MLP with 100%, 31%, and 55% sensitivity, specificity and quality index respectively.

This result insight that recurrent model enhancing the performance of CNN for imbalance classification can be conducted by using recurrent model or data augmentation by GAN. However, the combination of adding recurrent model and data augmentation may not enhance the model performance. On the opposite, it decreases the performance of the model.

TABLE III. RESULT OF SCENARIO 3: MODEL PERFORMANCE ON VARIATION OF AUGMENTATION DATA

Reference	Data Augmentation	Model	Sensitivity	Specificity	Quality Index
this study	No	CNN1D+LSTM	96.623	47.368	**67.652**
this study	X_train[class1]	CNN1D	93.617	47.154	**66.441**
this study	X_train[class1]	Resnet1D	89.628	48.78	**66.122**
[7]	No	RBF-SVM	100	33	**57.446**
[7]	No	MLP	100	33	**57.446**
[7]	No	R.Forest	100	31	**55.678**

V. CONCLUTION AND FUTURE WORKS

In this study we enhanced convolutional neural network by using recurrent model or data augmentation via GAN for wearable ECG signal quality assessment. Adding recurrent model to CNN increase its performance by approximately 3% margin in un-augmented dataset. Generating fake samples from “unacceptable” class can enhance CNN performance up to 2% margin. Combining recurrent model and data augmentation perform not good performance in this study. However, it doesn’t close the feasibility to combine those two approaches.

There are several opportunities to develop the ECG signal quality assessment system. First, we plan to exploring the other recurrent model e.g. bidirectional LSTM, RNN, C-RNN etc. Second, we plan to explore the other version of GAN e.g. conditional GAN (C-GAN) an AC-GAN. Third, we plan to explore the variation od loss function and optimizer.

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