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CNN Based Atrial Fibrillation Diagnosis with ECG Signals

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Abstract

Background/Objectives: Atrial Fibrillation (AFib), one of the arrhythmias, causes the atrium to beat irregularly. AFib can be diagnosed by observing electrocardiogram (ECG) signals. However, the degree of irregular running depends on the patient, and it is difficult to detect AFib in early patients. As a result, it is important to accurately judge Sinus Rhythm (SR) and AFib, and only doctors with extensive experience in cardiology are known to judge accurately. In this paper, we propose a convolutional neural network (CNN) to perform accurate AFib diagnosis from ECG signals.

Methods/Statistical analysis: The proposed AFib diagnostic technique has the following characteristics. The proposed artificial neural network consists of three layers CNNs and a fully connected layer. The final decision uses an ensemble of five models to reduce the deviation from the decision results and increase the decision accuracy. The design and performance verification of the proposed CNN diagnostic technique is based on Python TensorFlow 2.0.

Findings: Diagnostic performance is evaluated using ECG signals obtained from real-world normal people and patients with AFib. The evaluation results show an accuracy of approximately 96.25%, 98.72% sensitivity, and 93.39% specificity. Furthermore, we analyze using Gradient-Class Activation Mapping (Grad-CAM) what part of ECG signals the proposed CNN distinguishes AFib rhythm from SR.

Improvements/Applications: The proposed technique can be used as a method to accurately diagnose patients with AFib only with ECG signals without the help of a doctor. It could also be applied to a variety of wearable healthcare devices to diagnose AFib around the clock.

Keywords: AFib, ECG, Convolutional Neural Network, Model Ensemble, Grad-CAM

1. Introduction

Atrial Fibrillation (AFib) is a type of arrhythmias in which the atrium does not run regularly or beats very fast, 300 to 600 times per minute [1]. Symptoms of atrial fibrillation range from asymptomatic to palpitations, chest pain, shortness of breath and dizziness, depending on the incidence, ventricular rhythm, accompanying conditions, ventricular function and complications [2]. It is important to diagnose it accurately early because it is known to develop into a myocardial infarction or stroke. Types of AFib can be divided into paroxysmal AFib and chronic AFib [3]. In the case of paroxysmal AFib, the duration is short, and you may experience dizziness or fainting intermittently. In paroxysmal AFib patients, sinus rhythm (SR) is usually maintained, but suddenly AFib occurs and the heart beat is very fast. Those patients often visit the hospital with palpitations, difficulty breathing, and chest pain. In the case of chronic AFib, diagnosis may be possible only when AFib occurs and diagnosis is difficult if the moment is not detected. Paroxysmal atrial fibrillation is not at a serious level, but if it is not detected early and the symptoms persist, it can worsen into chronic AFib [4]. AFib is diagnosed by observing the elecctrocardiogram (ECG). It is common for AFib rhythms to show a clear difference from SR in ECG, but some atrial fibrillation rhythms are difficult to distinguish from SR, making it difficult to make an accurate diagnosis. Doctors with a lot of experience in large hospitals can make accurate diagnosis, but doctors with short experience always have the possibility of misdiagnosis.

This paper proposes a novel technique for diagnosing AFib using convolutional neural network

(CNN), a type of artificial neural network [5][6]. CNNs are known to perform well on the classification problem of images. In this paper, we apply 1 demention-CNN (1D-CNN) because ECG signals can be viewed as 1D images [7][8]. Specifically, the proposed CNN takes ECG signals in a 30-second interval as input. The CNN consists of a three-layer convolutional neural network and a fully connected layer. The final output is a binary classifier with two classes: SR and AFib. Model ensembles are utilized to reduce performance degradation and performance [9]. The proposed technique employs five model ensembles. In addition, we analyze which part of the ECG signal and distinguishes between AFib rhythm and SR using gradient-class activation mapping (Grad-CAM) [11]. For the ECG data, a total of 236 SR signals and 268 AFib signals are used for training and validation [12]. 75% of the data is used for training and the remaining 25% is used for performance evaluation. Cross-validation is used to produce optimal results [12]. Final performance evaluation shows an accuracy of about 96.25%. Therefore, the proposed atrial fibrillation diagnosis technology allows accurate atrial fibrillation diagnosis using ECG signals without the help of experienced doctors. If this technology is applied to wearable devices such as smart bands and smart watches, it is expected that it will be able to accurately diagnose AFib that occurs intermittently.

2. OFDM Radar Systems and Signal Model

The development process of the AFib diagnostic technique proposed in this paper is shown in Figure 1. ECG signals are measured through ECG devices, and the signals are used as input of the proposed. The measured ECG signals is inflated by data augmentation techniques, and data cross validation is performed. At this time, cross-validation proceeds not only by original dataset, but also by augmented dataset. We also utilize model ensembles to reduce performance degradation and deviation. The final output of the proposed CNN predicts AFib or SR, and shows the significant impact on the prediction in the corresponding ECG via Grad-CAM.

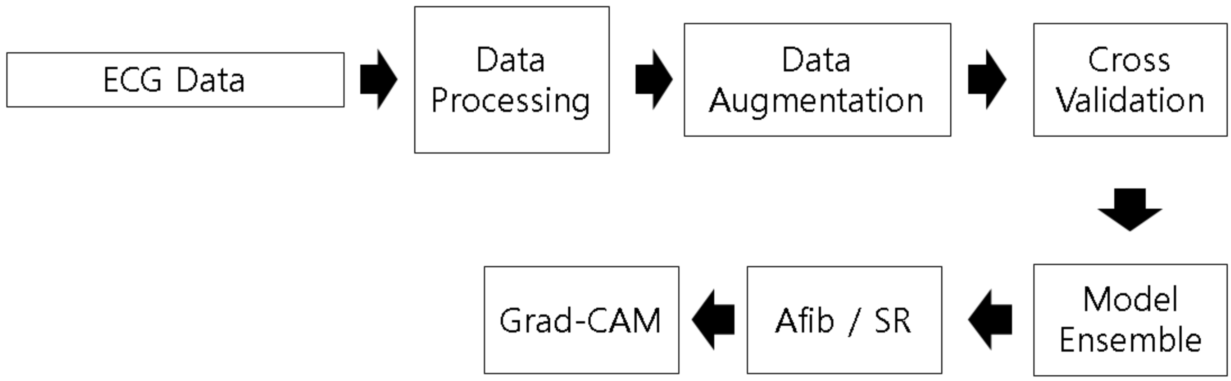

Figure 1. Block diagram of proposed AFib detection

2.1. Data Processing

In this paper, data processing is performed to make the original ECG signals into data that can be used for training. This work involves data segmentation, data scaling, and data separation for cross-validation. The processing of data is performed on MATLAB and CNN training and verification are conducted using Python Tensorflow 2.0.

2.1.1. Data Sampling

We proceed with data processing using MATLAB to make ECG data one-dimensional data for CNN training. The original ECG data are 236 SR people and 268 AFib patients for approximately 15 minutes per patient. The sampling frequency of the ECG signals is 50 Hz, and the diagnosis is performed by observing 30 seconds ECG signals. In other words, one signal used for diagnosis is 1,500 samples (50 Hz x 30 seconds = 1,500).

2.1.2. Data Augmentation

Data augmentaion techniques are used to prevent overfitting and achieve better performance during learning. Data augmention is an effective method used when the number of data is scarce. In this paper, when an ECG signal is divided into 30 seconds and made into one data, the data augmentation is performed by overlapping and cutting it. Overlapping strides are four: 5, 10, 15, and 30. Data augmentation is shown in Figure 2. In Figure 2, (a) produces data without overlapping regions with a stride of 30 seconds. For (b), (c), and (d), respectively, the strides are set to 15, 10, and 5s. The shorter the strides, the larger the overlapping region, and more data can be obtained. This data augmentation allows us to obtain twice, three times, and six times the data in (a), respectively. Data augmentation are used only for CNN training and not for performance verification.

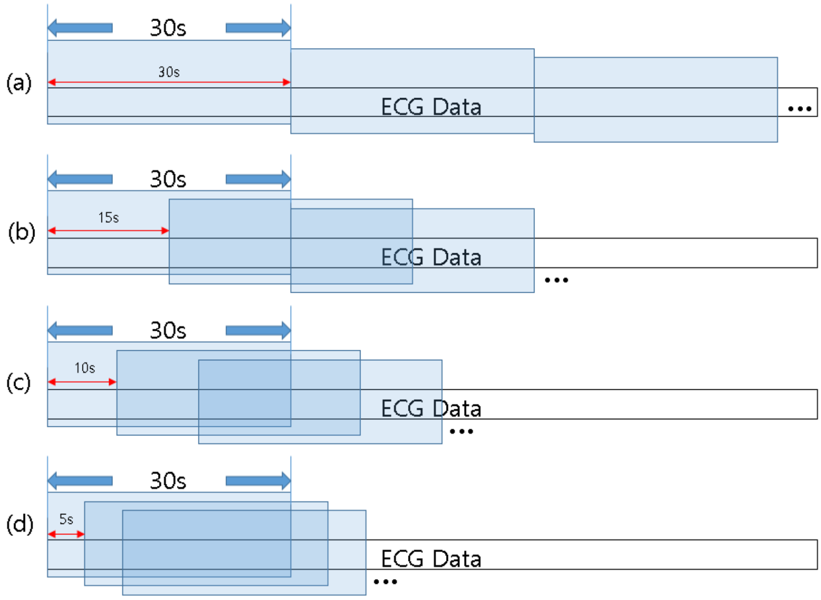

Figure 1. Description of data augmentation

2.1.3. Cross Validation

Next, a learning dataset and a test dataset are made for cross-validation. For cross-validation, 75% of the total data is used for training and 25% is for test. Thus, a total of four combinations of datasets are created. Figure 3 shows the results of creating a dataset of four combinations.

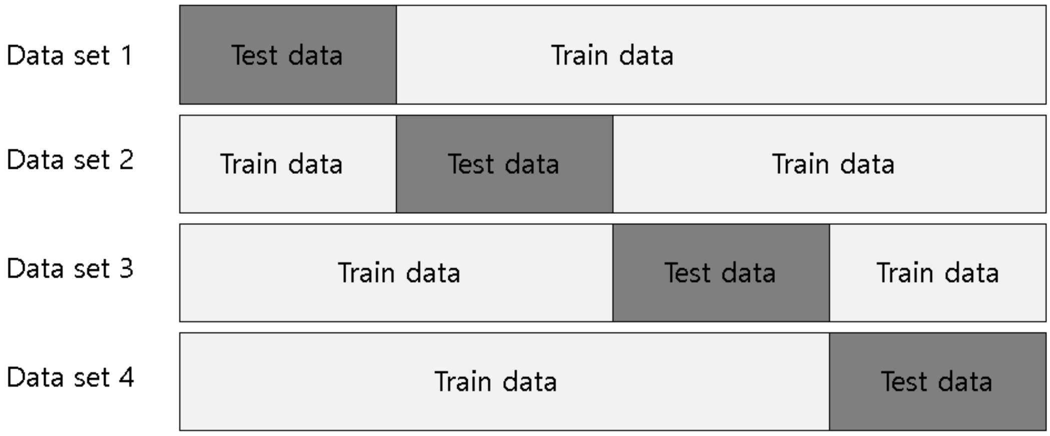

Figure 2. Combination of data set split

For each data set, the number of augmented data is shown in Table 1.

Table 1. The Number of Data Set by Stride

	Stride(s)	5	10	15	30
Data Set 1	Train	61,653	30,923	20,680	10,507
	Test	4,192	4,192	4,192	4,192
Data Set 2	Train	66,751	33,487	22,399	11,314
	Test	3,325	3,325	3,325	3,325
Data Set 3	Train	66,122	33,177	22,187	11,219
	Test	3,420	3,420	3,420	3,420
Data Set 4	Train	64,455	32,340	21,629	10,937
	Test	3,702	3,702	3,702	3,702

2.2. CNN design

This paper proposes a novel technique for diagnosing AFib using CNN, a type of artificial neural network. CNNs are known to perform well on the classification problem of images. This paper applys 1D-CNN because ECG signals can be viewed as one-dimensional images. The proposed CNN consists of a three-layer convolutional neural network and a fully connected layer. The final output of the designed CNN is a binary classifier with two classes: SR and AFib.

The structure of the proposed CNN in this work is shown in Figure 4. The proposed CNN consists of a convolutional neural network of three layers and a fully connected layer. In the first layer, the input data is 1x1500 and the 1x4x32 convolutional filter is used with 1x1 stride to obtain the output of 1x1500x32. It then passes through the 1x4 max pooling layer with 1x1stride to obtain an output size of 1x375x32. In the second layer, it takes the output of the first layer as input and apply the same size of convolutional operations and max pooling. With 1x4 max pooling applied, the output size is 1x93x32. In the third layer, the convolutional filter is changed into 1x32x64. max pooling applies equally to the preceding two layers. The size of the signal passed to the third layer is 1x23x64. The images that pass through the third layer is converted into one-dimensional signals using the flatten layer. The size of the one-dimensional signal created is 1,474, which is 23x64. It goes to a fully connected layer and the output is a 1x2 signal. Finally, a softmax decides SR or AFib.

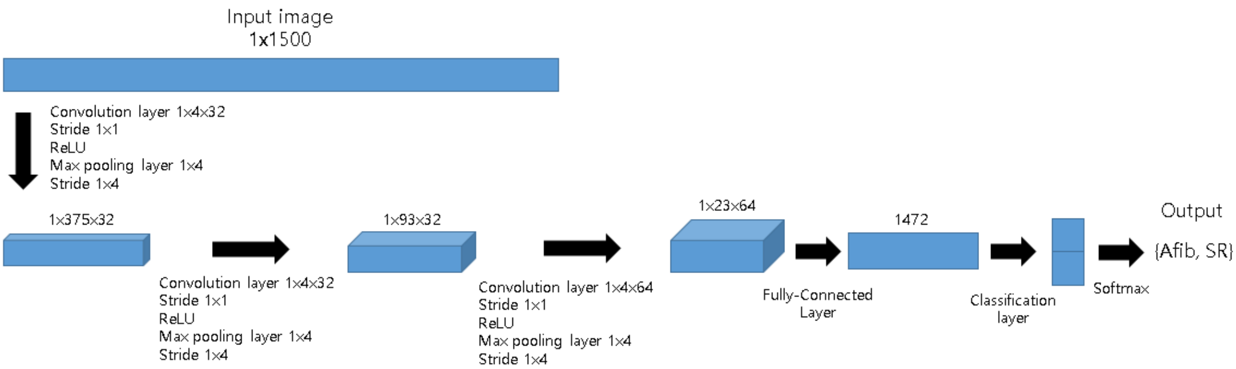

Figure 3. Proposed CNN Structure

2.3. Model Ensemble

This paper applies model ensembles to reduce performance degradation and performance deviation based on initial values. Model ensembles are one of the techniques that combine multiple CNN classifiers to perform better than one CNN classifier. In this paper, five CNN models are independently trained, and all of the outputs are used to obtain final result by majority vote. The structure of the proposed model ensemble is shown in Figure 5.

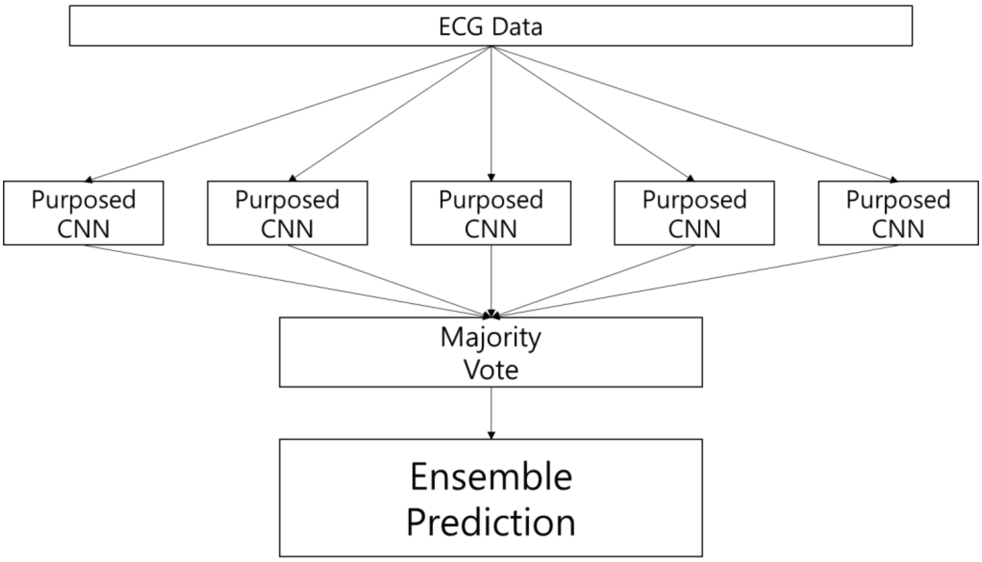

Figure 4. Proposed Model Ensemble Structure

2.4. Grad-CAM

We analyze using Grad-CAM which part of the proposed CNN looks at and distinguishes atrial fibrillation rhythm from SR. Unlike CAMs that require Global Average Pooling (GAP), Grad-CAM is a way to obtain CAM without using GAP. Although CAM can only be found in feature maps that take GAPs, Grad-CAM can be used to determine which factors affect prediction not only in the last layer but also in the input and middle layers. Grad-CAM obtains the slope between the predicted class and each convolutional layer output to express the location that has had a large impact. The formula for Grad-CAM is as follows.

$$L^{c}{}_{Grad-CAM}(i,j) = ReLU(\sum_k a^c{}_k f_k(i,j)), \quad (1)$$

$$a^c{}_k = \frac{1}{Z}\sum_i \sum_j \frac{\partial S^c}{\partial f_k(i,j)} \quad (2)$$

where $a^c{}_k$ is the average impact of $f_k(i,j)$ on class c of $k-th$ feature map. In other words, $a^c{}_k$ is obtained by GAP with slope from the former layer.

3. Performances

This section performs training and performance verification using the proposed CNN, model ensembles, and Grad-CAM described in the previous section. First, the optimal dataset and data stride time are found through cross-validation that produces the best performance. Next, we apply model ensembles using optimal parameters found in cross-validation, and reduce performance deviations and degradation. Performance evaluation indicators are prioritized in order of sensitivity, accuracy, and specificity. The reason for prioritizing sensitivity over specificity is that accurately predicting patients is more important than accurately predicting normal people. Finally, we present the feasibility and analytical feasibility of models designed by applying Grad-CAM.

3.1. Training

Training is performed using the designed CNN. The training environment uses Python 3.7.5 version running on the NVIDIA GeForce RTX 3080. The hyper parameters are as follows. Set Epoch to 300 and mini-batch size to 1024. Optimization technique is Adagrad with a learning rate of 0.001. The cross entropy is used as a loss function. Table 2 shows training results by dataset and by stride.

Table 2. Learning Result by Data Set and Stride

	stride time(s)	5	10	15	30	Avg.
Data set 1	Acc.	95.42	95.70	95.53	93.46	95.02
	Sen.	98.28	98.64	99.54	98.28	98.68
	Spec.	92.22	92.63	91.06	88.09	91.00
Data set 2	Acc.	95.24	95.12	94.70	93.86	94.73
	Sen.	95.96	96.13	95.84	96.48	96.10
	Spec.	94.46	94.04	93.46	91.01	93.26
Data set 3	Acc.	98.04	97.45	97.77	97.57	97.70
	Sen.	99.55	99.21	99.77	99.71	99.56
	Spec.	96.39	95.54	95.60	95.23	95.69
Data set 4	Acc.	97.64	97.43	96.24	95.92	96.80
	Sen.	99.49	99.59	99.74	99.64	99.61
	Spec.	95.53	94.95	92.22	91.64	93.58
Avg.	Acc.	96.58	96.42	96.06	95.20	96.06
	Sen.	98.32	98.39	98.72	98.52	98.48
	Spec.	94.65	94.29	93.08	91.74	93.44

The analysis in Table 2 shows that the mean accuracy of all data is 96.06%, sensitivity is 98.48% and specificity is 93.44%. The best-performing stride is 15 seconds, shows 96.06% accuracy, 98.72% sensitivity, and 93.08% specificity. Figures 6 and 7 show the loss curve and the accuracy curve obtained during the training of Stride 15, respectively. As seen in Figure 6, loss converges at epoch 280. The convergence loss value is about 0.066. For training accuracy, about 97.6 % is observed. These results confirm that the learning has been performed well.

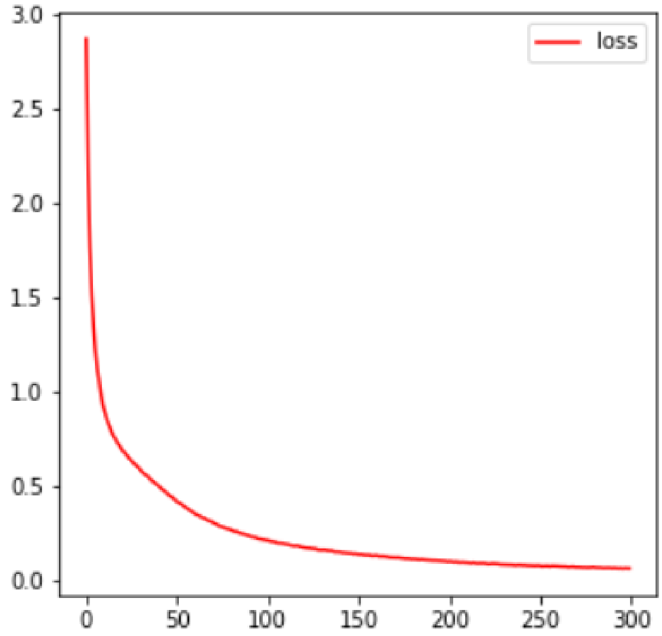

Figure 5. Learning curve for loss

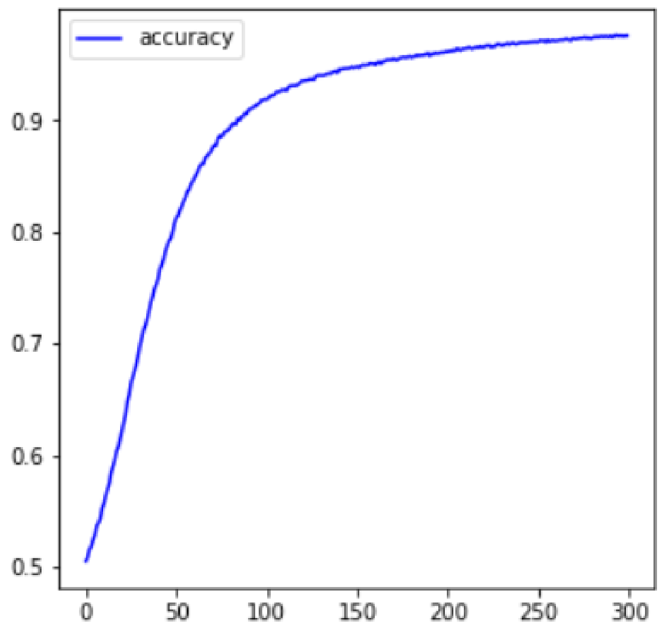

Figure 6. Learning curve for accuracy

3.2. Verification

This section proceeds cross-validation by dataset and by stride. Table 3 shows verification results by dataset and by stride. As a result of cross-validation, the mean accuracy of all data is 95.92%, sensitivity 98.33%, and specificity 93.75%. At Stride 10, which has the best performance, the accuracy is 96.25%, sensitivity is 98.72%, and specificity is 93.39%. Given that there is no significant difference between training and verification performances, it can be seen that overfitting has not occurred. Figures 8 and 9 show verification loss curves and verification accuracy curves, respectively, obtained in Stride 10. The verification loss shows its lowest value of 0.14 at epoch 150, and the verification accuracy shows 96.6% at epoch 150.

Table 3. Verification by data set and stride

	stride time(s)	5	10	15	30	Avg.
Data set 1	Acc.	95.41	94.96	94.63	93.15	94.53
	Sen.	99.04	98.95	98.32	97.96	98.56
	Spec.	91.37	90.51	90.51	87.79	90.54
Data set 2	Acc.	95.66	95.00	94.85	94.19	94.92
	Sen.	95.27	96.82	95.79	95.32	95.80
	Spec.	96.10	93.02	93.84	92.96	93.98
Data set 3	Acc.	97.66	98.09	97.57	97.51	97.70
	Sen.	99.94	99.32	99.83	99.04	99.53
	Spec.	95.17	96.76	95.11	95.84	95.72
Data set 4	Acc.	96.75	96.75	96.65	97.40	96.88
	Sen.	99.79	99.79	99.64	98.48	99.42
	Spec.	93.27	93.27	93.21	96.17	93.98
Avg.	Acc.	96.37	96.25	95.92	95.17	95.92
	Sen.	98.51	98.72	98.39	97.70	98.33
	Spec.	93.97	93.39	94.48	93.17	93.75

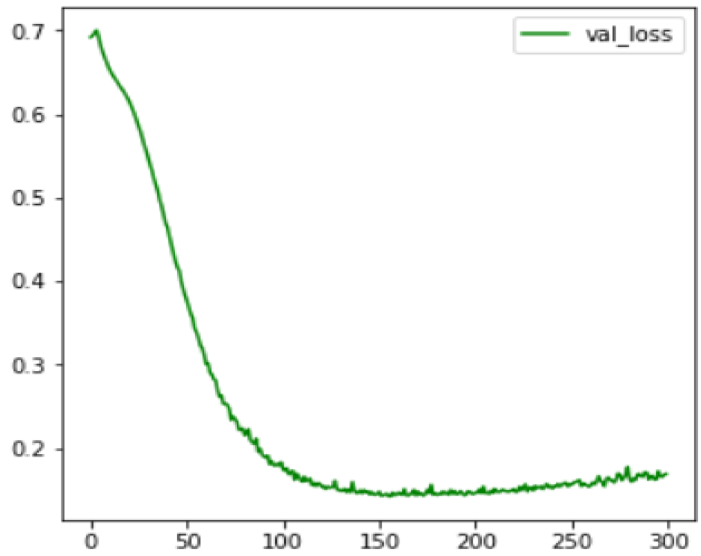

Figure 7. Verification Loss Curve

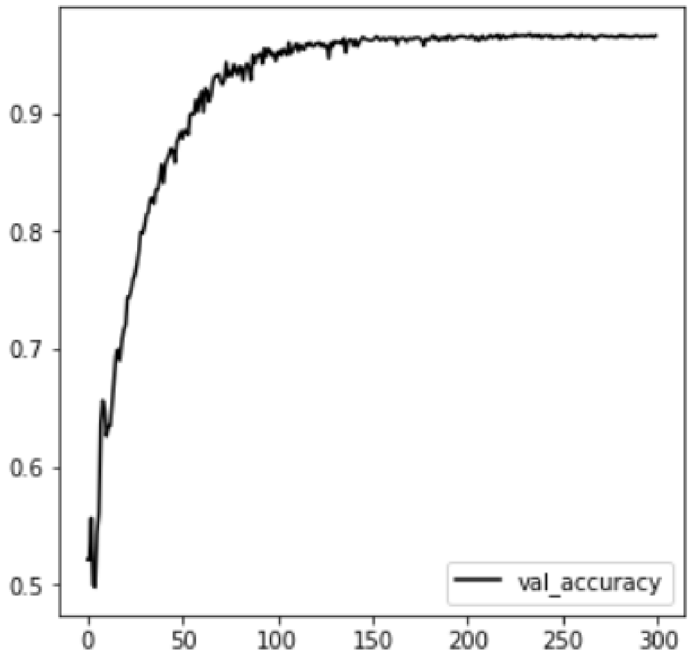

Figure 8. Verification Accuracy Curve

3.3. Grad-CAM Result

This section uses Grad-CAM to find the regions that influenced the prediction results. We observe a fully connected layer using Grad-CAM. As a result of Grad-CAM, the output is obtained at each sample in the data and displayed in blue the closer to zero and red the closer to one to see which sample of importance is high and low. The red color can be seen as a part that greatly affects prediction. A total of 1,500 points, consisting of 1x1,500, are colored and overlaid with original ECG signal. This shows which part of ECG has a significant impact on the prediction. Figure 10 shows the application of Grad-CAM in the fully connected layer of SR and atrial fibrillation, respectively.

Specifically, (a) shows the application of Grad-CAM to SR ECG, and (b) shows the application of Grad-CAM to AFib ECG. AFib shows particularly high weights at 800 and 1,200 samples. This means that ECG signals at that point had a significant effect on predicting AFib. However, in the case of SR, it can be seen that all ECG signals are observed evenly, not at specific samples. From these results, SR appears to be predicted by observing all intervals, rather than judging with a small part.

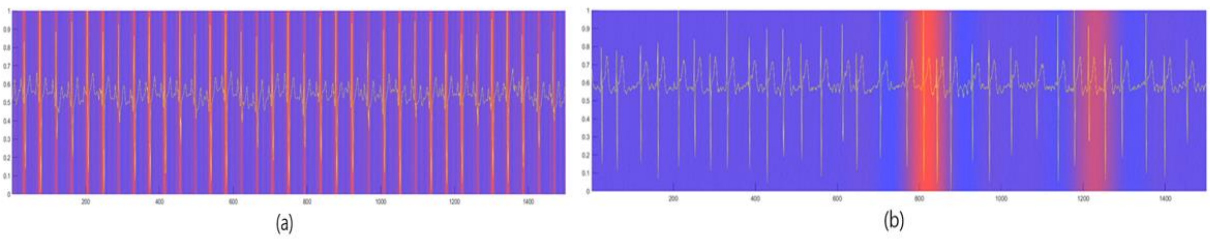

Figure 9. Grad-CAM of SR(a) and AFib(b)

4. Conclusion

In this work, we proposed a novel AFib diagnosis technique using CNN. The proposed technique first performs data augmentation and cross-validation to find the appropriate data set for CNN. Then, we proposed a 1D-CNN structure to classify SR or AFib, and using the dataset, the CNN training was carried out. The proposed CNN consists of 3 convolutional layers and 1 fully connected layer, which is relatively simple neural network. To reduce performance deviation and degradation, a five-model ensemble technique was also employed. Grad-CAM was employed to observe which parts largely impacts on the prediction. Performance verification results using ECG signals confirm that the accuracy of the proposed technique was 96.25%, sensitivity was 98.72%, and specificity was 93.39%. Especially the sensitivity was better than the specificity, which means that the proposed CNN can detect AFib patient accurately. Therefore, if the proposed technique is applied to real-world medical sites, patients with atrial fibrillation can be determined with high accuracy using ECG signals alone without any help of a doctor. Due to its good performance, the proposed technique could be applied to various wearable healthcare devices to diagnose atrial fibrillation 24 hours a day.

5. References

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