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**August 2022**

**Doctor's Degree Thesis**

**Development of Lightweight Ensemble  
Network for Detecting Heart Disease Using  
ECG Signals**

**Graduate School of Chosun University**

**Department of IT Fusion Technology**

**Siho Shin**

# **Development of Lightweight Ensemble Network for Detecting Heart Disease Using ECG Signals**

심전도 기반 심장 질병 검출을 위한  
앙상블 네트워크 개발

August 26, 2022

**Graduate School of Chosun University**

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# **Development of Lightweight Ensemble Network for Detecting Heart Disease Using ECG Signals**

**Advisor: Prof. Youn Tae Kim**

This thesis is submitted to The Graduate School of  
Chosun University in partial fulfillment of the  
requirements for the Doctor's degree.

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**Graduate School of Chosun University**

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This is to certify that the Doctor's Thesis of  
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has been approved by the Examining Committee for the thesis  
requirement for the Doctor's degree in IT Fusion Technology.

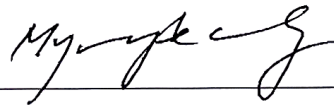
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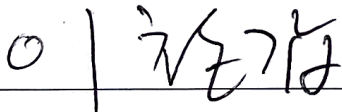
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## Acronyms

ECG	Electrocardiogram
BN	Batch normalization
ReLU	Rectified Linear Unit
FC	Fully Connected
CPU	Central Processing Unit
CNN	Convolutional Neural Network
BiLSTM	Bidirectional Long Short-Term Memory
LSTM	Long Short-Term Memory
NSR	Normal Sinus Rhythm
AFIB	Atrial Fibrillation
PVC	Premature Ventricular Contraction
LBBS	Left Bundle Branch Block Beat

1-NN	1 Nearest Neighbor
VA	Ventricular Arrhythmias
SE-ResNet	Squeeze-and-Excitation Residual Network
ResNet	Residual Network
GLCM	Gray-Level Co-occurrence Matrix
GLRLM	Gray-Level Run-Length Matrix
FIR	Finite Impulse Response
MSE	Minimum Square Error
ROC	Receiver Operating Characteristic
TPR	True Positive Rate
FPR	False Positive Rate
TNR	True Negative Rate
AUC	Area Under the ROC Curve

SNR

Signal-to-Noise Ratio

## 요 약

### 심전도 기반 심장 질병 검출을 위한 앙상블 네트워크 개발

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심장병은 증상이 나타나면 신속히 치료해야 한다. 심장 질병을 검출하는 머신 러닝 기법은 데스크탑 컴퓨터가 필요하며 이것은 주기적으로 건강을 확인해야 하는 환자에게 치명적인 단점이 될 수 있다. 본 연구에서는 모바일 환경에서 쉽고 빠르게 작동할 수 있는 부정맥 진단을 위한 Federated learning 및 MobileNetV2-BiLSTM 기반 앙상블 알고리즘을 제안한다. 짧은 시간에 측정된 심전도(ECG) 신호는 Matching pursuit 알고리즘을 이용하여 데이터를 증강하며 이를 이용하여 향상된 부정맥 분류 정확도를 달성하였다. 부정맥 데이터는 MobileNetV2와 BiLSTM을 결합한 앙상블 분류기를 통해 분류되었다. 이 알고리즘을 사용하여 데이터를 분류함으로써 91.7%의 정확도를 달성했다. 알고리즘의 성능은 Confusion matrix와 ROC curve를 사용하여 평가하였다. 민감도, 특이도, 정밀도, F1 score는 각각 0.92, 0.91, 0.92, 0.92였다. 제안된 알고리즘은 오랜 시간동안 심전도 신호를 측정하지 않기 때문에 바쁜 현대인들의 건강관리를 용이하게 한다. 또한, Federated learning 방식을 도입하여 데이터 하이재킹 문제에 대한 해결 가능성을 확인하였으며, 이 알고리즘은 모바일 건강관리, 객체 감지, 텍스트 인식 및 인증에 적용될 수 있다.



# I. Introduction

## 1.1. Research background

Biosignals are indicators of physical health that allow the management of various diseases, such as muscle pain, insomnia, and heart disease [1-3]. The electrocardiogram (ECG) is the most important signal for confirming the state of the heart [4,5].

In an ECG, the heartbeat is represented by electrical signals. The heart rate of a healthy person is usually between 60 and 100 beats per minute [6]. When a person is exercising, tense, or excited, the heart beats faster. There are typically no problems in such cases; however, when the heart beats irregularly for no reason, this symptom is called arrhythmia. According to NHANES 2015-2018 data, the prevalence of cardiovascular disease (comprising coronary heart disease, heart failure, stroke, and hypertension) in adults  $\geq 20$  years of age is 49.2% overall (126.9 million in 2018) and increases with age for both males and females. The prevalence of cardiovascular disease excluding hypertension is 9.3% overall (26.1 million in 2018) [7]. The rapid increase in the number of heart disease patients due to changes in eating habits and reduced exercise has contributed to the most serious death rate for modern people. The most representative type of heart disease is arrhythmia. Early detection of arrhythmia is crucial, because arrhythmia causes symptoms such as dizziness, fainting, chest pain, and difficulty breathing, and can lead to heart attacks [8].

Methods of diagnosing arrhythmia include periodically visiting a hospital or using a Holter monitor. However, both of these are inconvenient for patients and can be expensive. In addition, ECG signals measured by widely used smart watches are acquired over a short period of  $< 1$  min; therefore, it is impossible to identify cardiovascular diseases, including arrhythmia, using such devices.

Methods for detecting arrhythmia include detection of early contraction of the ventricles using the RR interval [9], analysis using the discrete Fourier

transform [10,11], and analysis based on the Hilbert transform [12,13]. These arrhythmia diagnosis methods must be performed by a specialist, and for the early detection of heart disease, a large quantity of ECG data must be checked for irregular events. In addition, there are many factors to be considered for accurate diagnosis, such as the patient's movements and signal interference problems that occur when ECG signals are measured during normal activities [14]. Furthermore, the "silver generation" and residents of mountainous areas or islands cannot visit the hospital often, owing to a lack of transportation, physical aging, or disease.

To overcome these difficulties, we propose an arrhythmia detection algorithm combining MobileNetV2-BiLSTM and a matching pursuit algorithm that can accurately diagnose arrhythmia using ECG data. To increase the accuracy of the algorithm, the ECG signal in the time domain was converted to the frequency domain using a scalogram.

Because the proposed algorithm augmented ECG data using matching pursuit, it was possible to accurately detect arrhythmia through ECG signals measured within a short timeframe by learning a large quantity of data. The proposed algorithm used the ECG database provided by MIT-BIH [15,16]. An experiment was conducted for increasing the classification accuracy using a small quantity of data. The number of data used in the algorithm is 654, with approximately 164 data per class. For training algorithms, this scale of data is insufficient. To solve this problem, the matching pursuit algorithm is used, which can decompose data or duplicate data. The matching pursuit algorithm can eliminate noise because it can approximate the signal. By combining MobileNetV2-BiLSTM and matching pursuit and applying the proposed algorithm to ECG signals, we confirmed the possibility of developing an efficient health management algorithm applicable to mobile devices.

## 1.2. Key technology

MobileNetV2 is an image classification model that was proposed in 2018 [17]. It is a lightweight network that preserves performance to the greatest extent possible, and compared with previously proposed networks, the size of the classifier model is significantly reduced by applying the average pooling technique in the process of converting the feature group into the classifier group. The feature stage has a structure in which convolutional modules are repeatedly stacked. MobileNetV2 has a conv. + batch normalization (BN) + rectified linear unit (ReLU) structure, and the computational burden and model size are reduced by using a depth-wise convolutional layer as an intermediate layer. In the process of converting spatial information into a fully connected (FC) layer, the weight of the FC layer is limited to the number of channels by applying average pooling rather than the existing tensor shape conversion [18].

In a previous study, computed tomography and X-ray data related to COVID-19 were classified using six different models, including MobileNetV2 [19]. The model performance was evaluated according to the accuracy, precision, recall, and F1 score. Among the models tested, MobileNetV2 and VGG19 exhibited the best performance.

There are many reports of heart disease diagnosis using machine learning. A review was conducted to identify the trends of machine learning-based and data driven techniques for heart disease diagnosis with imbalanced data [20]. A meta analysis was performed using 451 reports acquired from reputed journals between 2012 and 15 November 2021.

Machine learning, which can accurately classify data, uses a high performance central processing unit (CPU); thus, it has excellent computational processing power and uses multiple high performance graphics. Because machine-learning algorithms are developed with a focus on performance, the operating environment of the algorithm is not considered. However, patients with heart disease must check their health regularly and can not carry a high

performance desktop. To solve this problem, a machine learning method that can be implemented on a mobile device is required. MobileNetV2 is a convolutional neural network (CNN)-based algorithm designed for applications wherein the computational resources are limited or the battery performance is important.

BiLSTM is a circulating neural network that can process data that change over time, such as video [21,22]. The original circulating neural network had the problem of data loss after repeated backpropagation, but BiLSTM mitigates the problem of data loss using a forget gate. The core of the BiLSTM neural network comprises the sequence input layer and the long short-term memory (LSTM) layer. The sequence input layer inputs sequence or time series data into the neural network. The LSTM layer learns the data according to the sequence time flow.

The matching pursuit algorithm was developed to linearly decompose signals in order to understand their characteristics. When the original signal is decomposed, the characteristics of the original signal are identified by considering the time and frequency domains simultaneously, e.g., the wavelet and Fourier transforms, in the order of energy [23].

The wavelet transform is a multi resolution system capable of processing signals in various frequency bands by converting the input sampling frequency into another set of sampling frequencies. By applying this transform to an ECG signal, noise removal and waveform segmentation can be performed simultaneously, providing a high resolution for each feature element in the signal. The wavelet transform can be used to analyze the converted signal in the desired frequency band by multiplying the input signal by the wavelet function and scale function, and dividing the frequency band into high and low frequency segments [24-26].

The MIT-BIH database, which is widely used in arrhythmia related studies, contains ECG data categorized into 17 classes. This dataset consists of ECG signals with durations of 10 s from 45 participants. The MIT-BIH database is commonly used by researchers to develop heart related algorithms [27-29].

Table 1 presents details regarding the databases used in this study.

Data Index	Data Class	Number of Data
1-283	Normal sinus rhythm (NSR)	283
284-418	Atrial fibrillation (AFIB)	135
419-551	Premature ventricular contraction (PVC)	133
552-654	Left bundle branch block beat (LBBB)	103

Table 1.1. Datasets used in this study.

Figure 1.1 shows the ECG signals included in the database. “NSR” corresponds to a normal ECG signal. AFIB is one of the heart diseases that can be detected using ECG signals. PVC and LBBB correspond to premature ventricular contractions and left bundle branch block beats, respectively, and also represent abnormal heartbeats.

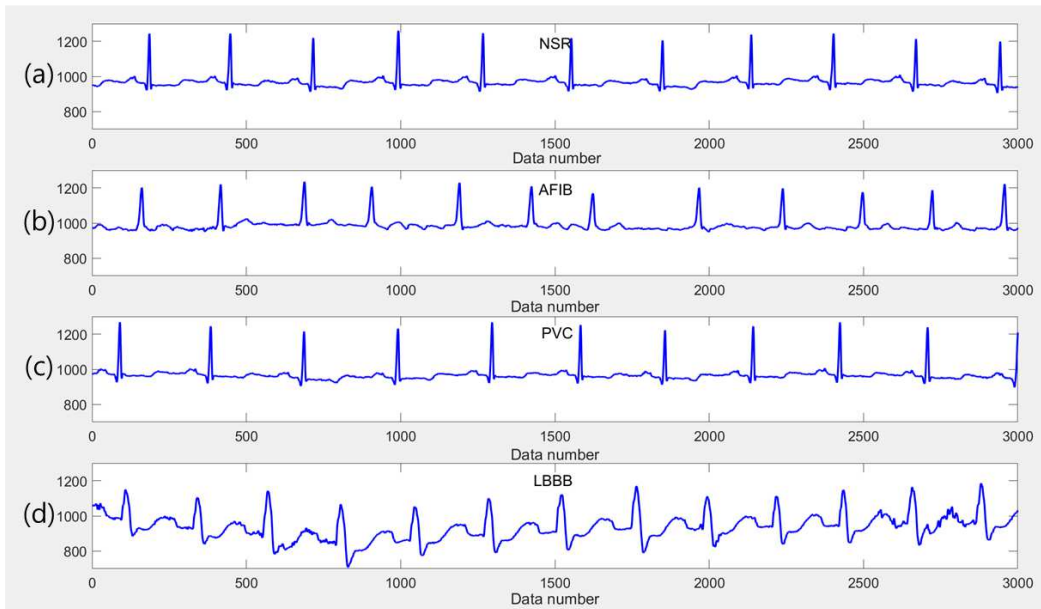


Figure 1.1 MIT-BIH database contained several ECG signals. The recordings were digitized at 360 samples per second per channel with a resolution of 11 bits: (a) NSR; (b) AFIB; (c) PVC; (d) LBBB. Two or more cardiologists independently annotated each record.

### 1.3. Previous study

Tuncer et al. [2] classified arrhythmia signals using the 1D-HLP technique. Using the 1D-HLP, 512 dimensional features are extracted from each of the five levels of the low-pass filter. These features are subjected to 1 Nearest Neighbor (1-NN) classifier for classification with four distance metrics. The authors obtained a classification accuracy of 95.0% when classifying 17 arrhythmia classes using the MIT-BIH arrhythmia ECG Database.

Ribeiro, H.D.M, et al. [30] proposed an algorithm that could classify the ECG signal of both healthy and sick people. The proposed lightweight solution uses quantized one-dimensional deep convolutional neural networks, and is ideal for real time continuous monitoring of cardiac rhythm. It is capable of providing one output prediction per second. It is accurate (sensitivity of 98.5% and specificity of 99.8%) and can be implemented on a smartphone, which is energy efficient and fast, requiring 7.65 ms per prediction

Naz et al. [31] proposed a new deep learning approach for the detection of ventricular arrhythmias (VA). Initially, the ECG signals were transformed into images, and this had not been done before. Subsequently, these images were normalized and utilized to train the AlexNet, VGG-16, and Inception-v3 deep learning models. The results were evaluated on the MIT-BIH Database, and an accuracy of 97.6% was achieved.

Cai et al. [32] developed a deep learning-based approach for multi label classification of ECG, named Multi-ECGNet, which can effectively identify patients with multiple heart diseases simultaneously. The experimental results show that these methods can achieve a high score of 0.863 (micro-F1-score) in classifying 55 types of arrhythmias.

Park et al. [33] proposed an ECG signal multi classification model using deep learning. The authors used a squeeze-and-excitation residual network (SE-ResNet), a residual network (ResNet) with a squeeze-and-excitation block. The authors compared SE-ResNet with ResNet as a baseline model for various

depths of the layer (18/34/50/101/152). The SE-ResNet classifier with 152 layers achieved an F1 score of 97.05% for seven class classifications. The model surpassed the baseline model, ResNet, by +1.40% for seven class classification.

Lee et al. [34] proposed a novel method for generating a gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM) from one-dimensional signals. The authors extracted the morphological features for automatic ECG signal classification. The extracted features were combined with six machine learning algorithms to classify cardiac arrhythmias. Of the six machine learning algorithms, combining XGBoost with the proposed features yielded an accuracy of 90.46%, an AUC of 0.982, a sensitivity of 0.892, a precision of 0.900, and an F1 score of 0.895, and presented better results than wavelet features with XGBoost.

Existing technology for arrhythmia diagnosis makes it difficult for patients to detect diseases in their daily lives. This is due to structural problems with the arrhythmia diagnosis technology. When deep learning is used to detect arrhythmia it involves a very large amount of computation, because it is developed with a focus on performance. This deep learning computer uses high performance GPUs and memory. However, it has spatial limitations because it is not portable. Although arrhythmia diagnosis technology is being developed, it is not practically helpful for patients with arrhythmia. To solve these problems, patients need solutions to be available on mobile devices that are now widely available to many people.

## II. MobileNetV2-BiLSTM algorithms

### 2.1. Preprocessing

Figure 2.1 shows the workflow of the proposed algorithm. The proposed arrhythmia detection method involves preprocessing to minimize noise and resize the ECG signals. To increase the accuracy of the algorithm, the training data were sufficiently selected through the matching pursuit algorithm. The wavelet transform was used for feature point extraction. Arrhythmia was detected using a MobileNetV2-BiLSTM neural network.

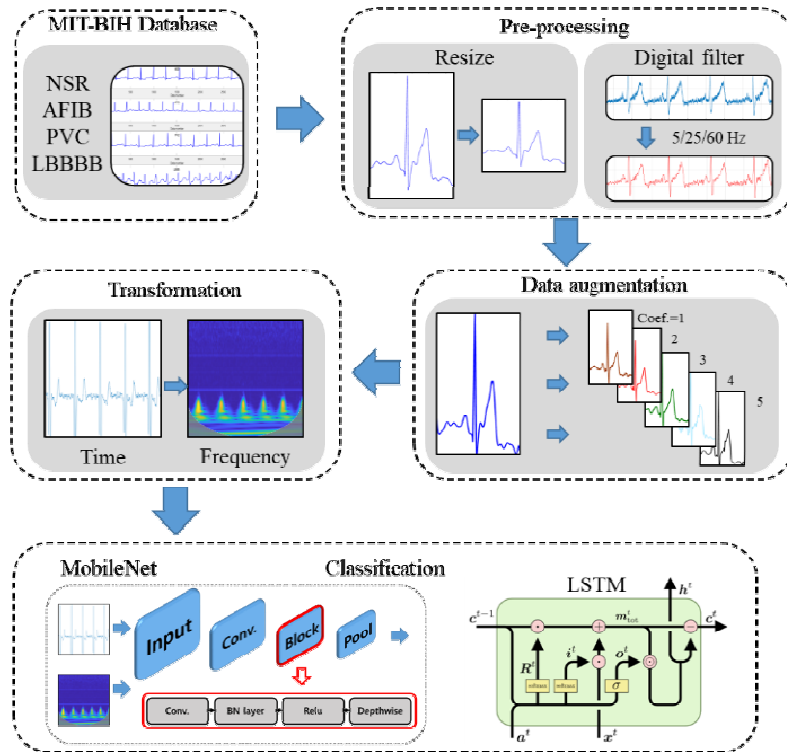


Figure 2.1. Workflow of the proposed algorithm. This algorithm randomly replicates ECG signals and classifies them into four classes using MobileNetV2 and BiLSTM. The data were duplicated using a matching pursuit algorithm. Time domain data were converted to frequency domain using wavelet transforms.



Noise in ECG signals is caused by various factors, such as the environment, whether the electrodes are in good contact with the patient, movement of the measurement cable, movement of the baseline due to breathing, and movement of the patient. These factors affect the shape and size of the waveform, reducing the accuracy of arrhythmia detection. To minimize noise, a Butterworth notch filter and a moving average filter were designed. Figure 2.2 shows the signal processing results.

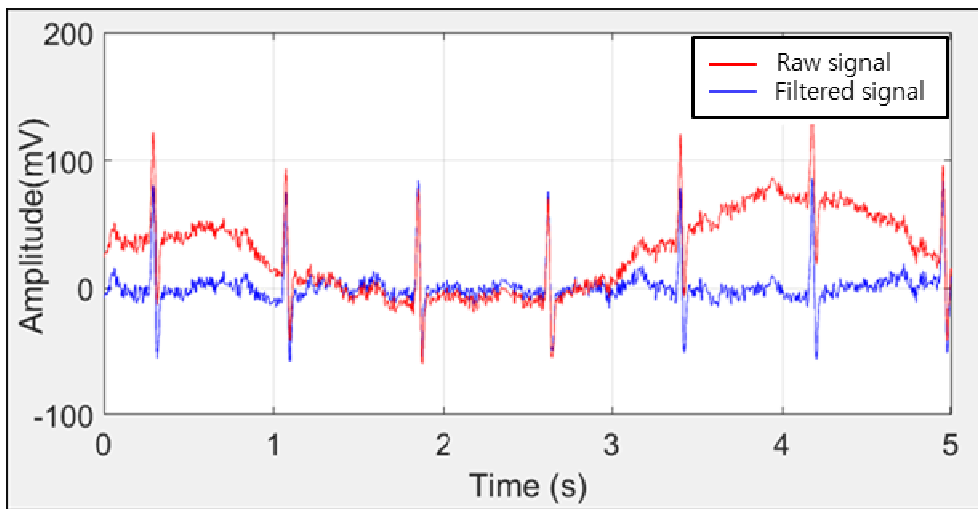


Figure 2.2. Digital filter was designed in MATLAB and applied to the ECG. Butterworth high-pass and low-pass filters were designed (5–250 Hz), and a band-stop filter was used to reduce the noise at 60 Hz.

## 2.2. Data augmentation

A matching pursuit algorithm was used to augment the training data. This algorithm can generate additional signals that are similar to the original signal.

The original signal must be decomposed to generate a similar signal. First, the basic signals  $g_0$  and  $a_0$  that most closely reflect the original signal are calculated, as follows:

$$F(t) = a_0 g_0(t) + R(t) \quad (1)$$

where  $R(t)$  represents the remainder of the original signal after it is decomposed using the base signal  $g_0$ , and  $a_0$  is a coefficient that optimally represents the given signal in terms of the minimal mean square error given any base signal  $g_0$ . The approximated signal that best represents a given original signal has the smallest error value when approximating the original signal. Therefore, to determine this basic signal function and the coefficient value, we define Equation (2), which gives the difference between the original signal and its approximation.

$$E(a_0|g_0) = \langle f - a_0|g_0, f - a_0|g_0 \rangle \quad (2)$$

Finding the coefficient  $a_0$  that minimizes Equation (2), this becomes an optimal value from the viewpoint of the least square error. The minimized  $E(g_0|g_0)$  is given as

$$E(a_0|g_0) = \langle f f \rangle - \langle f, g_0 \rangle^2 \quad (3)$$

To minimize Equation (2), the default signal with the maximum value of  $\langle f, g_0 \rangle^2$  and the default signal with the largest inner product absolute value are set to the signal  $g_0$  to decompose the input signal. For minimizing Equation (2), the expansion coefficient  $a_0$  is expressed as follows:

$$a_0 = \langle f, g_0 \rangle \quad (4)$$

Equations (2)–(4) are used to determine the basic signal with the largest absolute value of the original signal and the inner product. This procedure represents the input signal using a basic signal that is most similar to the

original signal. After a given input signal is decomposed, the original signal is redefined using the approximate error signal  $f(t)$ , as indicated by Equation (5). This procedure is repeated until the original signal is completely decomposed. Thus, the matching pursuit algorithm decomposes the original signal into appropriate basic signals.

$$f(t) \leftarrow (f(t) - a_0 g_0(t)) \quad (5)$$

Figure 2.3 shows the results of generating a signal similar to the original signal by changing the coefficient.

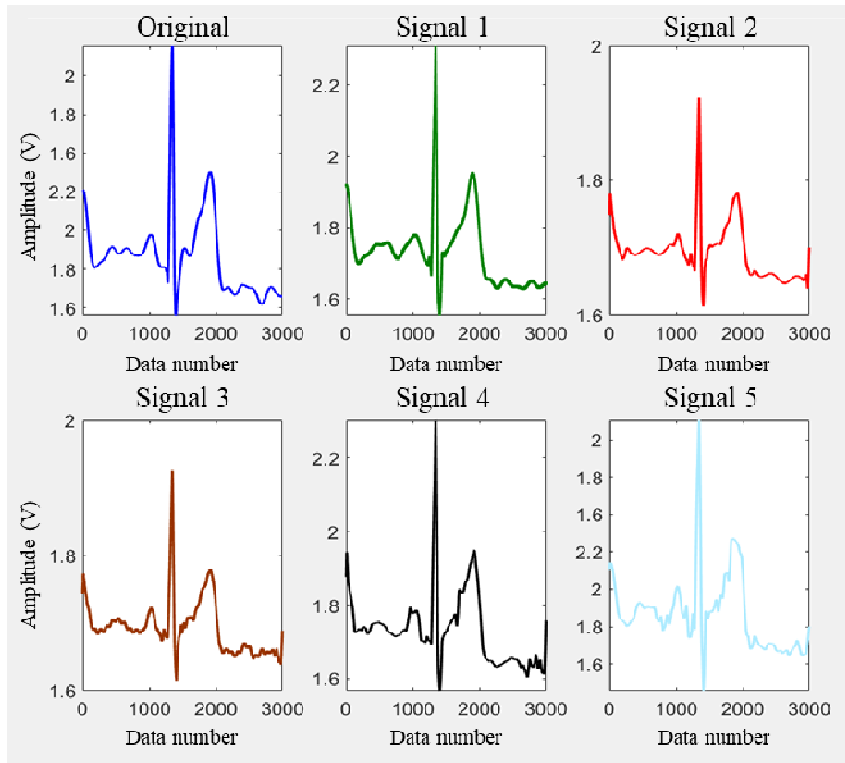


Figure 2.3. ECG signals generated by the matching pursuit algorithm. The matching pursuit algorithm generates a correlation matrix obtained through the inner product and selects values in the order such that the correlation size is the largest. The matching pursuit algorithm uses this value to output similar signals.

## 2.3. Wavelet Transform

Equation (6) represents the wavelet function  $\psi(a, d)(x)$  using the scale coefficient  $a$  and the transition element  $d$ .

$$\Psi(a, d)(x) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \Psi\left(\frac{t-d}{a}\right) dt \quad (6)$$

The discrete signal  $x(n)$  of the ECG can be converted into a discrete wavelet by discretizing the scaling element ( $a$ ) and the transition element ( $d$ ) in Equation (6). At the level  $j = -1$ , it can be expressed by combining a high frequency signal  $D_{2^j}[x(n)]$  and a low frequency signal  $A_{2^j}[x(n)]$ . The ECG signal is expressed as  $[x(n)] = D_{2^j}[x(n)] + A_{2^j}[x(n)]$  and generally satisfies Equations (7) and (8).

$$D_{2^j}[x(n)] = \sum_{k=1} D_{2^j}(k) \Psi_{2^j}(n - 2^j k) \quad (7)$$

$$A_{2^j}[x(n)] = \sum_{k=1} A_{2^j}(k) \Psi_{2^j}(n - 2^j k) \quad (8)$$

In this case,  $2^j$  indicates that the number of samples is divided by two as the level  $j$  decreases. Equation (7) represents a signal with a high frequency component, which is related to the transition elements of the signal. Equation 8 shows the low frequency component of the signal, which is related to the scale of the signal. The high and low frequency components of the input signal are divided according to the level  $j$ .

$D_k$  (detail) is the finite impulse response (FIR) high-band filter coefficient associated with the wavelet coefficient, and  $A_k$  (approximation) is the FIR low-band filter coefficient associated with the scale function coefficient. The signal whose length is reduced by half through each filter is repeatedly converted to the next scale level. The wavelet coefficient indicates the similarity to the wavelet generating function. This represents the frequency signal. Figure 5 shows the results of applying the wavelet transform to the ECG signal.

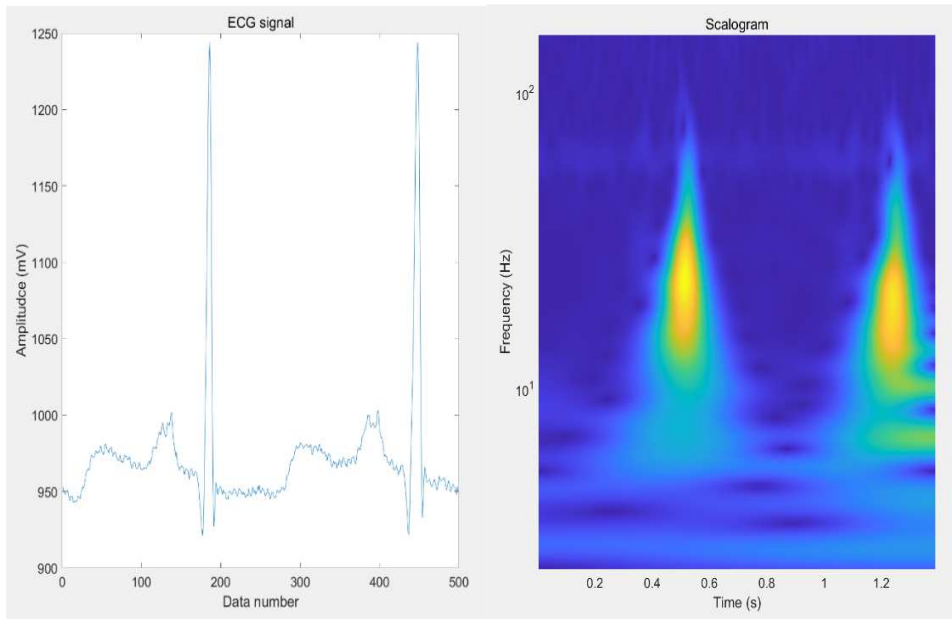


Figure 2.4. Scalogram was used to investigate the frequency characteristics of the ECG signals. A higher voltage of the signal corresponded to a clearer scalogram result. (a) ECG signal; (b) scalogram of the ECG signal.

## 2.4. Proposed ECG Signal Classification method

An algorithm combining MobileNetV2 and BiLSTM was developed for classifying arrhythmia data. MobileNetV2 classified the arrhythmia data, and BiLSTM maintained the sequence data to improve the performance of the arrhythmia classification model. A diagram of the MobileNetV2-BiLSTM algorithm for classifying arrhythmia data is shown in Figure 2.5.

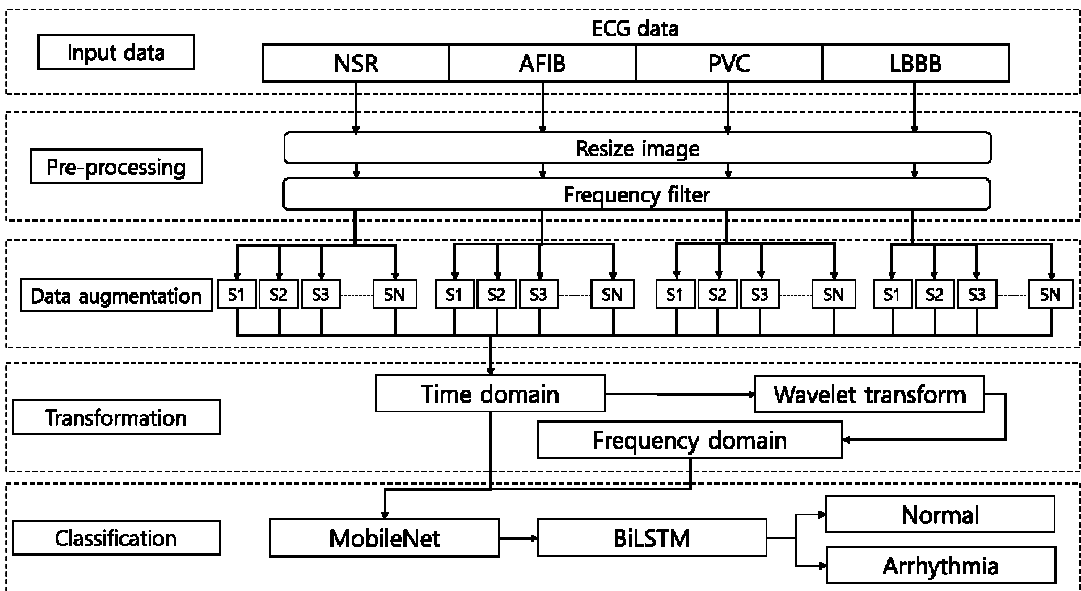


Figure 2.5. Diagram of the proposed algorithm. The input data consisted of four classes, and a MATLAB-based digital filter was used for preprocessing. The matching pursuit algorithm was used for data augmentation. MobileNetV2-BiLSTM was applied in the data classification process.

The data ratio was the highest with 283 NSR data and the lowest with 103 LBBB data. The balance data may cause overfitting problems, because the number of data is insufficient. To solve this problem, data were added using the matching pursuit algorithm in this study.

The matching pursuit algorithm was developed to decompose signals in order to understand their characteristics. During the decomposition of the

signal to be analyzed, the time and frequency domains are simultaneously considered by applying the wavelet transform or Fourier transform.

When a signal is added, the matching pursuit algorithm first determines the length of the signal to be added. Subsequently, a signal that most closely reflects the original signal is generated. At this time, the minimum square error (MSE) is used. A smaller MSE corresponds to a higher degree of similarity to the original signal. In the above formula,  $g_0$  represents a basic signal, and  $a_0$  represents a signal with a minimized MSE.  $R(t)$  represents the signal remaining after the original signal is decomposed using  $g_0$ . A matching pursuit function can be applied to the original signal to generate several signals with small MSE values. MobileNetV2 extracts random features from the input data. Figure 2.6 shows the MobileNetV2-BiLSTM structure.

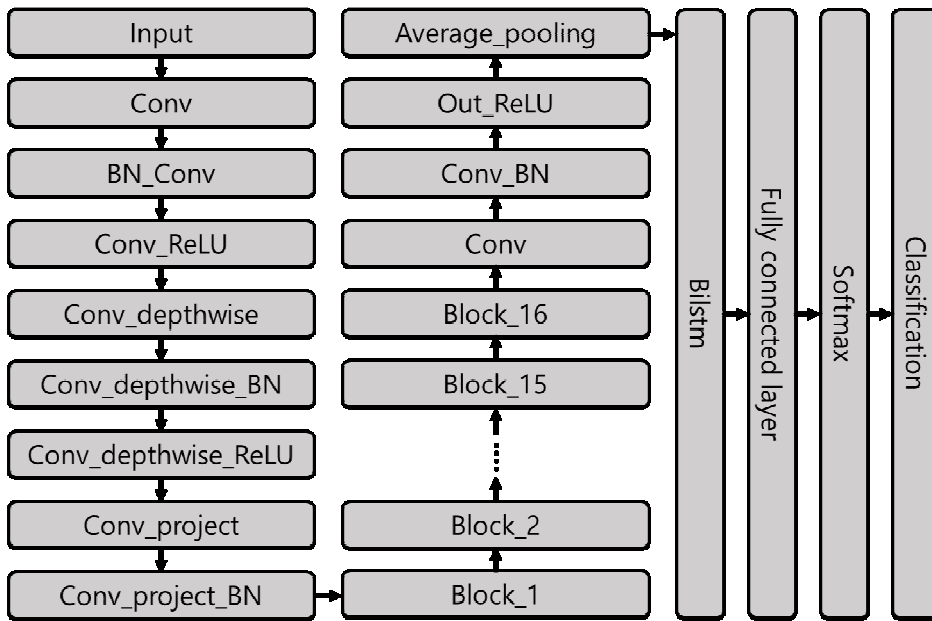


Figure 2.6. MobileNetV2-BiLSTM structure for classifying data. ECG data are input to BiLSTM through a convolution operation and classified in the FC layer. MobileNet V2 and BiLSTM were combined by Matlab-based Network designer.

The input size was  $227 \times 227 \times 3$ . The data size was changed to  $114 \times 114 \times 32$  by applying a stride of  $2 \times 2$  in the first convolutional layer. BN and ReLU functions were applied, and subsequently, depth-wise convolution ( $3 \times 3 \times 1$ ), BN, the ReLU function, and convolution were applied to reduce the amount of computation.

MobileNetV2 contains 16 blocks, and all the blocks were implemented in the same manner, as shown in Figure 2.7.

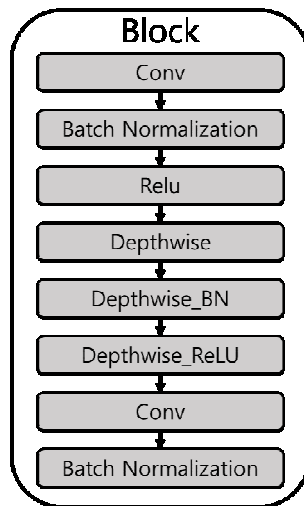


Figure 2.7. Block included in MobileNetV2. The block performs the resize process and convolution of the input data. Normalization is performed in blocks so that algorithms can process data. MobileNetv2 has 16 interconnected blocks.

Because sequence data processing is difficult with general neural networks, a special recurrent neural network was used for BiLSTM. Each LSTM layer has three gates that transmit or control data and can learn by considering the gradient decay problem. LSTM obtains the information of all the cells over time. However, data cannot be learned after the cell in which the current learning is in progress. BiLSTM is an improved version of LSTM, in which forward propagation and backpropagation are used to learn information implied



in the past and future, respectively. Consequently, this model can handle time series data more efficiently. Figure 2.8 shows the structure of the BiLSTM model.

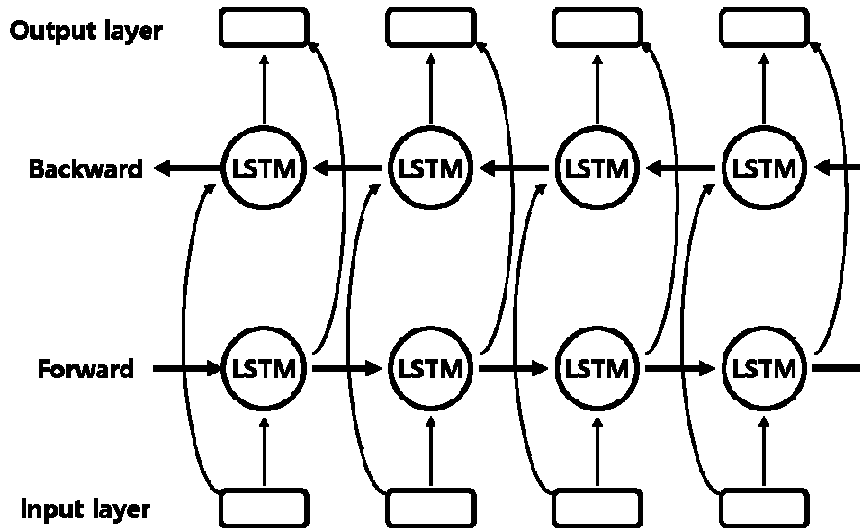


Figure 2.8. Architecture of BiLSTM. A bidirectional LSTM (BiLSTM) layer learns bidirectional long-term dependencies between time steps of time series or sequence data. These dependencies can be useful when you want the network to learn from the complete time series at each time step.

The first LSTM layer was used to calculate the sequence information at the current time. The second layer was used to read the same sequence in the reverse direction and add reverse sequence information to extract meaningful features of the input data. The output value between the LSTM layers was transmitted to not only the adjacent unit but also the input of the next LSTM layer. The weight of the LSTM could be updated by the forward and backward propagation of the neuron. After the characteristics of each input signal were extracted, a BiLSTM classification model was configured. Dropout was added to the BiLSTM layer to prevent overfitting of the model. The learning results were used as inputs to an FC layer. The ECG signal was classified in the FC layer, and a softmax layer was used to output the result.

Figure 2.6. (a) Output voltage and current with different resistors as external loads. (b) Dependence of the output power on external load resistances.

## 2.5. Performance Evaluation

The sensitivity, specificity, precision, and F1 score were calculated to evaluate the performance of the presented model. Sensitivity refers to the percentage of data that are actually positive and are classified as positive. The sensitivity of the proposed model was calculated as 0.92 using Equation (9).

$$Sensitivity = \frac{TP}{P} = \frac{TP}{TP + FN} \quad (9)$$

Specificity refers to the ratio of negative data classified as negative. The specificity of the proposed model was calculated as 0.91 using Equation (10).

$$Specificity = \frac{TN}{N} = \frac{TN}{TN + FP} \quad (10)$$

Precision refers to the ratio of data whose predicted value and actual value match as positive among subjects whose prediction is positive. It indicates how well positive data are classified. The precision of the proposed model was calculated as 0.92 using Equation (11).

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

The F1 score is the most representative method for evaluating the performance of deep learning classification models. The proposed model exhibited high F1 scores, as the precision and sensitivity were not biased toward either side.

$$F1\ score = 2 * \frac{Precision * Sensitivity}{Precision + Sensitivity} \quad (12)$$

### III. Federated learning algorithms

#### 3.1. Federated learning based Arrhythmia detection

Federated learning is a deep learning technology that uses multiple local models and one global model. Each local model learns data and then transmits the parameters of the local model to the global model. The global model can obtain optimal results by aggregating parameters to update the model and sharing this model with the local model. Federated learning can reduce communication problems due to low traffic volume because only parameters are transmitted. This can also complement the data leakage problem. Therefore, it is suitable for the field of health diagnosis using a mobile device.

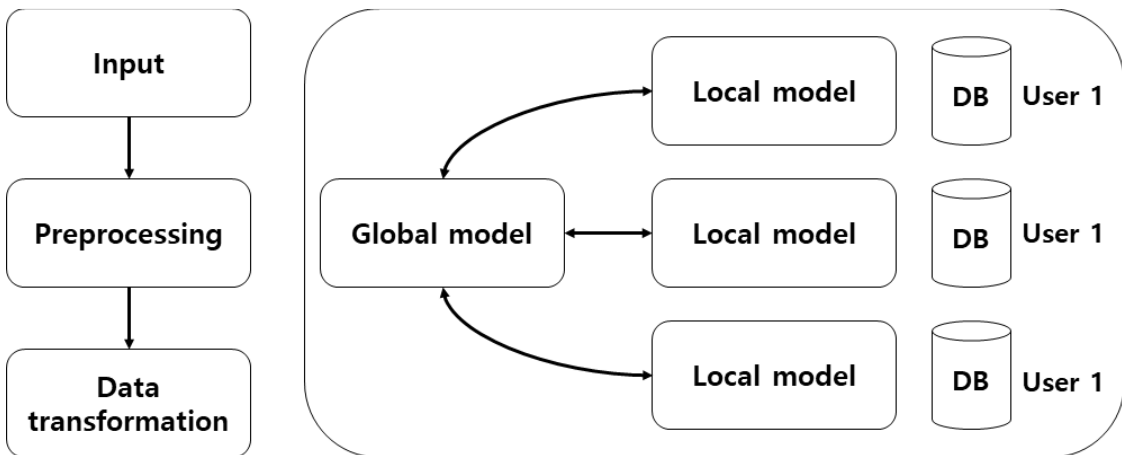


Figure 3.1. Structure of Federated learning

##### 3.1.1. MobileNet

This algorithm was implemented in Matlab's Deep Network Designer. MobileNetV2 has a convolutional layer, batch normalization, ReLU layer, and average pooling layer. After that, the data was processed in 16 blocks. BiLSTM uses forget gate to alleviate data loss problems. The fully connected layer that performs the correlation of the identified data with the original data through training. And the Softmax layer that determines the probabilities of



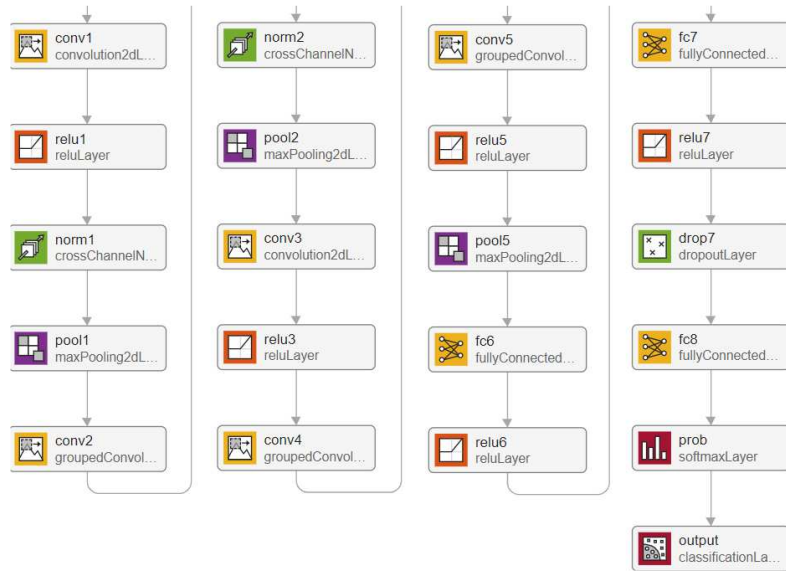


Figure 3.3. Structure of ANN V1

### 3.1.3. Artificial Neural Network V2

ANN V2, is pre-trained using image data. It consists of a convolutional neural network and has set the convolutional filter size to 3x3. By fixing the filter size to a size of 3x3, fewer parameters are generated, which improves the efficiency of learning. The input size is set to 227x227x3 like other Local models.

Layer	1	2	3	4	5	6	7	8
Kernel	3x3x3	3x3x64	3x3x64	3x3x128	3x3x256	3x3x256	3x3x256	3x3x256
Max pooling	1	2	*	2	*	*	2	*
Stride	1	1	1	1	1	1	1	1
Layer	9	10	11	12	13	14	15	16
Kernel	3x3x256	3x3x256	3x3x256	3x3x256	3x3x256	Flatten FC layer Dropout	FC layer Dropout	FC layer Softmax
Max pooling	*	2	*	*	2			
Stride	1	1	1	1	1			

Table 3.2 Layer of ANN V2

### 3.2. Parameter aggregation

Secure Aggregation is a computational protocol that goes through encryption so that the server cannot distinguish between updates from each participant. The server can only know the sum of the total values after receiving a certain number of updates from the devices. Secure Aggregation can be seen as a protocol that enhances privacy for security purposes, and information can be protected against attacks targeting central servers. When there is a server  $S$  and each device  $u$ , the device  $u$  sends and receives the  $k$ -dimensional vectors  $S_{u,v}, S_{v,u}$  to and from the server. In this case,  $P_{u,v} = S_{u,v} - S_{v,u} \pmod{R}$ .

Each device sends a  $Y_{u,v} = S_{u,v} - S_{v,u} \pmod{R}$  value to the server. The server can deliver updates to the server without exposing the data of each device by adding all the received values. The value added by the server is  $\bar{x} = \sum_{u \in P_{u,v}} (\pmod{R})$ .

## IV. Result and discussion

### 4.1. Result and discussion

Using the proposed model, i.e., the MobileNetV2-BiLSTM algorithm, 2000 ECG signals were classified. The data for each class were augmented to 500 using the matching pursuit algorithm. Figure 4.1 presents the classification results. As shown, the LBBB data were best classified among the four classes. This is because the LBBB data had the most prominent features, such as baseline fluctuations and changes in the QRS complex, among the ECG signals. The AFIB data exhibited an accuracy of 92.8%, and were also classified relatively well compared with the other data, because the signal interval was not constant and the signal amplitude was small. The NSR data had the lowest classification accuracy because they had no noticeable features compared with the other data.

**All Confusion Matrix**

<b>True value</b>	NSR	434 21.7%	36 1.8%	45 2.3%	19 0.9%	81.3% 18.7%
	AFIB	28 1.4%	464 23.2%	0 0.0%	0 0.0%	94.3% 5.7%
	PVC	38 1.9%	0 0.0%	455 22.8%	0 0.0%	92.3% 7.7%
	LBBB	0 0.0%	0 0.0%	0 0.0%	481 24.1%	100% 0.0%
		86.8% 13.2%	92.8% 7.2%	91.0% 9.0%	96.2% 3.8%	91.7% 8.3%
	NSR	AFIB	PVC	LBBB	<b>Predicted value</b>	

Figure 4.1. Result of classification using proposed algorithms



Figure 4.1. Results of arrhythmia detection using an ensemble network. Red color indicates cases of misclassification. Green indicates exact classification. Gray indicates the classification result. The values at the end of each row and column indicate accuracy and error rate.

The sensitivity of the proposed model was calculated as 0.92 using Equation (9). The specificity of the proposed model was calculated as 0.91 using Equation (10). The precision of the proposed model was calculated as 0.92 using Equation (11). The F1 score of the proposed model was calculated as 0.92 (on average) using Equation (12). Table 2 presents the performance of the proposed algorithm.

Data Index	Class	Sensitivity	Specificity	Precision	F1 Score
1	NSR	0.81	0.71	0.87	0.84
2	AFIB	0.94	0.98	0.93	0.94
3	PVC	0.92	0.97	0.91	0.92
4	LBBB	1	0.99	0.96	0.98
Average	-	0.92	0.91	0.92	0.92

Table 4.1. Algorithm performance evaluation results.

The receiver operating characteristic (ROC) curve is an important indicator for measuring the performance of classifiers [35]. It indicates how the true positive rate (TPR) changes when the false positive rate (FPR) changes. Here, the TPR represents the sensitivity. By setting the FPR as the X-axis and the TPR as the Y-axis, the changes in the TPR with respect to the FPR were examined. The true negative rate (TNR) is an indicator corresponding to the sensitivity.

The presented algorithm was trained by considering the following parameters. This set value was determined by conducting several experiments using MobileNet v2-BiLSTM and comparing the results.

Option	Value	Option	Value
Batch size	30	Time elapsed	23 m 30 s
Data rotation	5	Epoch	40
Data shift	3	Iteration	120
Validation frequency	50	Learning rate	0.01

Table 4.2. Algorithm performance evaluation results.

The batch size refers to the size of a group when the dataset used for training is divided into several groups. The training dataset is divided because it takes a long time to train if the entire dataset is entered into a neural network. The batch size used in this study was 30. Data rotation is a procedure applied to improve the efficiency when an algorithm learns. Neural networks have different learning outcomes depending on the state of data. When the same image is inputted differently, the neural network recognizes different data. (1) The normal image is the same as input (2), but the image is rotated. The data rotation used in this study was set to five. ‘Data shift’ refers to the movement of data in the pixels. Similar to data rotation, the input data can be completely different if they move by pixel size, which can improve the learning efficiency. The data shift for this algorithm was set to 3. Overfitting problems may occur in deep learning algorithms. To prevent this, a verification process is required, and in this study the verification was conducted 50 times.

‘Time elapsed’ refers to the time taken by this algorithm to classify the data. This algorithm classified the data in 23 m 30 s. An epoch means that the MobileNet v2-Bilstm algorithm learns all datasets once. The number of epochs of this algorithm was set to 40. Iteration refers to learning 1/n sized data once the entire dataset is divided into n equal parts. In the arrhythmia detection study, it was set as 120. The learning rate is the amount an algorithm can learn at once, and in this study, the learning rate was set to 0.01. If the learning rate is too large or too small, overfitting occurs; therefore, it is common to set it to 0.001 to 0.01.

Figure 4.2 shows the ROC curve for the MobileNetV2-BiLSTM algorithm. The higher the value on the left, the better the ROC curve. The ROC curve can be used to calculate the change in the TPR while changing the FPR from 0 to 1.

When the threshold is specified as 1, the FPR is 0, and conversely, when the threshold is 0, the FPR becomes 1. The TPR based on the change in the FPR value becomes the ROC curve.

The pseudo code below is a code that represents the behavior of the algorithm. The dataset used MIT-BIH. All signals were normalized to  $227 \times 227 \times 3$ , and Matlab-based digital filters were applied (5/250/60 Hz). Up to 250 pieces of each data were added using the matching pursuit. Since then, all data have been converted by applying Wavelet transform. As a result, the four classes contain 500 Time-Frequency domain data. A total of 2000 ECG data were classified using proposed algorithms.

Input data: MIT-BIH Database Output data: NSR, AFIB, PVC, LBBBB
<pre> 1. Create MIT-BIH Dataset 2.   for signal=0; signal&lt;654; n++ //(Number of data=654) 3.     Resize data(227x227x3) 4.     Digital Filter (5/250/60Hz) //Butterworth type 5.   end for 6.   for data=0; data&lt;250; data++ //data==data in each class 7.     Apply matching pursuit 8.     Save data in database 9.   end for 10.  for data=250; data&lt;500; data++ // All classes have 500 signals 11.    Apply wavelet transform 12.    Save data in database 13.  end for 14. Set up multi learning 15.   Parallel= Create a parallel pool with the same number of workers 16. Define the network architecture 17.   Layer=Input, Conv., ReLU, Pooling, FC, Softmax etc. 18.   Training Options=Epoch, Mini batch size, Iteration etc. 19. Train model 20.   for data=1; data&lt;2000; data++ 21.     Classification of data using proposed algorithm 22.     (1) The structure of the local model is updated with information            from the global model 23.     (2) All models calculate the average value of the parameter            every n times 24.     (3) The Average values apply to global models 25.     (4) Updated global models are evaluated for accuracy 26.     (5) This process is repeated until accuracy is improved 27.   end for </pre>

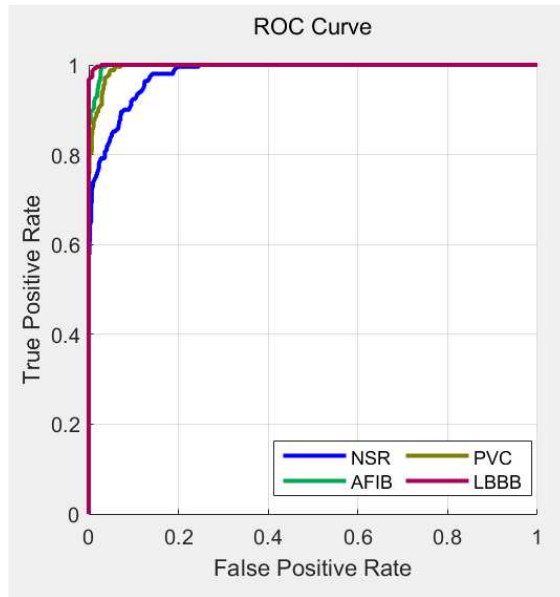


Figure 4.2. Arrhythmia detection results. A larger AUC corresponds to better performance. AUC denotes the area under the graph, and the four graphs represent the AUC that is proportional to the accuracy of each class.

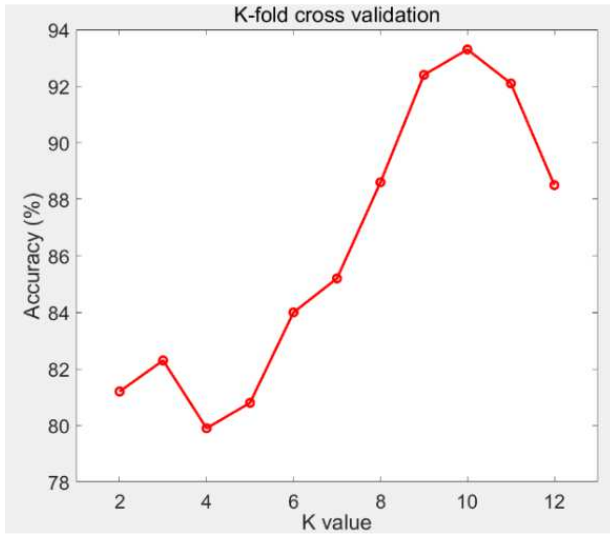
The area under the ROC curve (AUC) for each class indicated the performance of the classifier, with a larger area corresponding to a better performance. The AUCs for all the data are presented in Table 3.

<b>Class</b>	<b>AUC</b>
NSR	0.982
AFIB	0.997
PVC	0.996
LBBB	0.999
Average	0.994

Table 4.3. AUCs of the algorithm.

The PVC, LBBB, and AFIB data had AUCs close to 1, indicating that the

signals were classified accurately. The NSR data had an AUC value of 0.982, which was smaller than those of the other classes, but still indicates a high performance classifier (defined as having an AUC value of  $\geq 0.8$ ). Therefore, the NSR data were also classified accurately. Figure 4.3 shows the results of K-fold cross validation.



K value	Accuracy(%)
2	81.2
3	82.3
4	79.9
5	80.8
6	84
7	85.2
8	88.6
9	92.4
10	93.3
11	92.1
12	88.5

Figure 4.3. Results of K-fold validation for evaluating the classification performance of the algorithm. When the K value is equal to N, this algorithm performs the verification N times and calculates the average value for all the results. A K value of 10 yielded the best results. If the K value exceeds 10, the accuracy gradually decreases.

The most important goal of deep learning algorithms is “how accurately data can be classified.” In general, deep learning algorithms are used to predict unknown data with limited data held by the system. The accuracy increases with an increasing number of data. There is no problem if the data are sufficient, but when the system learns with limited data, it is important to use the data it holds as efficiently as possible. Cross validation reveals how efficiently the system can use data. Therefore, this method was used to verify the performance of the proposed algorithm.

The performance of the MobileNetV2-BiLSTM algorithm was analyzed

using K-fold cross validation. The dataset was divided into 12 groups, and one of the groups was extracted and used as the test set. The remaining 11 groups were used as training sets. The test was repeated 12 times.

The accuracy increased with the K value. The accuracy of the algorithm was maximized when the K value was 10, and it decreased as K increased further. The minimum accuracy was 79.7%, the maximum accuracy was 93.3%, and the average accuracy was 86.21%.

ECG signals contain noise. For example, noise caused by factors such as patient movement, impedance between the skin and electrodes, and movement of cables reduces the accuracy of the algorithm and should be minimized. In this study, a MATLAB-based Butterworth filter was designed. The filter band was set as 5 Hz for high-pass and 250 Hz for low-pass, and the band-stop filter was designed for 60 Hz.

Figure 4.4 shows the experimental evaluation results for the performance of the MATLAB-based filter. The raw signal with noise is shown in blue, and the result of applying the filter is shown in red. Comparing the two signals revealed that the noise of the baseline was reduced.

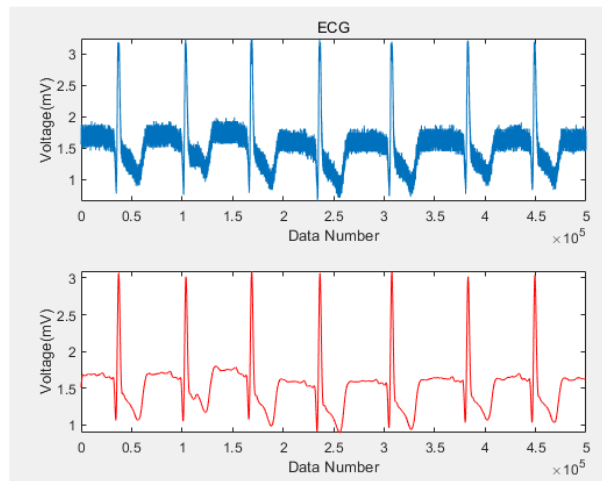


Figure 4.4. Noise removal using a MATLAB-based digital filter. The raw and filtered signals are shown in blue and red, respectively. The cutoff frequencies were set as 5, 250, and 60 Hz for low-pass, high-pass, and band-stop, respectively.

The digital filter was designed with general settings. Sometimes, the input data require a different filter band. For example, if another ECG study is performed using a different ECG database, the settings of the Butterworth filter used in this study must be changed. Alternatively, a filter other than the Butterworth filter may need to be used. Figure 4.5 presents ECG signals to which the Fourier transform was applied. The two ECG signals represent the results of the fast Fourier transform. They exhibit different frequency characteristics. Considering these frequency characteristics, the proposed algorithm should design an appropriate filter regardless of which ECG signal is input. The plan currently under consideration involves calculating the signal-to-noise ratio (SNR) of the signal and redesigning the filter when the SNR is too low.

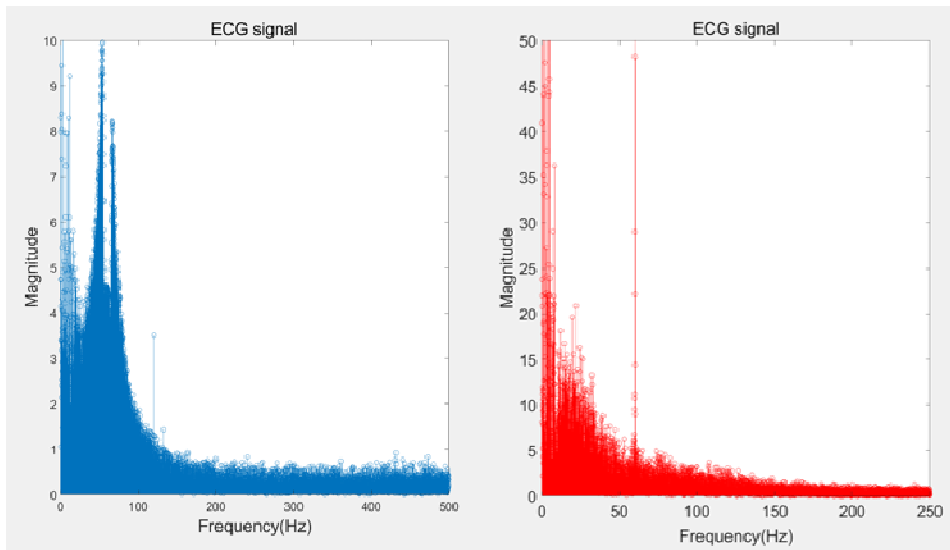


Figure 4.5. Fourier transform was applied to two ECG signals with different frequency characteristics. After applying digital filters to eliminate noise, Fourier transforms confirmed that the designed filter removed the signal in the appropriate frequency band.

The ECG signals used in this study were obtained from the MIT-BIH database. Digital filters were designed and applied to increase the classification accuracy. Subsequently, the learning data were sufficiently secured using the matching

pursuit algorithm. Data classification was performed using the MobileNetV2-BiLSTM algorithm.

The dataset used consisted of four classes, and the number of data was unbalanced. To solve this problem, the matching pursuit algorithm was used to analyze signals, adding 500 pieces of data from all classes. In this study, the proposed data augmentation method was used only to detect heart disease. However, if research on data aggregation progresses, we will be able to solve problems arising from unbalanced datasets. In addition, because the proposed method can arbitrarily add data measured in a short period of time, e.g., ECG signals, sufficient learning data can be secured, which can increase the algorithm accuracy.

The advantage of this algorithm is that arrhythmia diagnosis using a mobile device is possible. Deep learning, which has recently been used in various ways, has problems, such as the use of high performance CPUs and the consumption of large amounts of memory and power, because it focuses on performance. However, MobileNet is an algorithm designed for use in situations where the computational performance is limited; thus, it can solve the aforementioned problems.

The accuracy of the proposed model was 91.7%. Considering that the accuracy of the existing arrhythmia detection algorithm has reached approximately 99%, the performance of the proposed algorithm was not excellent. In addition to the accuracy, the sensitivity, specificity, and precision were poor compared with previous studies. However, the objective of the proposed method is to allow heart patients to check their health using mobile devices in their daily lives.

To overcome the disadvantages of this study, further research on the weight reduction of the model, the learning method of deep learning, and noise reduction is needed.

Khan, A. H et al detected heart disease using a single shot detection (SSD) MobileNet v2-based neural network. Dataset consists of four classes and includes one normal signal and three disease signals[18]. The input data was set lower than 300 KB in consideration of the learning time. SSD is used to detect the objects that can classify and local the objects in one step. This algorithm was implemented with the Tensorflow API and Google Colab. Batch size was set to 24



and training was performed 200000 times. The ratio of training and test was set to 8 to 2, and the learning rate was 0.0002. The accuracy of this algorithm was 98%.

Rincon, J. A et al. studied IoT-based monitoring systems for cardiovascular patients[36]. This system diagnosed atrial fibrillation using two MobileNet neural networks. The two MobileNet analyzed ECG signals in Time domain and Frequency domain, respectively. This study obtained more accurate results by analyzing signals in other ways. Dataset was divided into Training 8, Validation 1, and Test 1. Atrial fibrillation classes were accurately classified with a 90% probability.

The algorithm proposed in this study is aimed at detecting heart disease, as in previous studies using MobileNet. These studies have something in common that they used MobileNet. However, existing studies can output inaccurate results if learning data is not sufficiently secured.

Ahsanuzaman, S. M. et al. studied arrhythmia prediction models and real-time ECG surveillance systems[37]. To create an arrhythmia prediction model and an Android-based real-time ECG surveillance system, Long Short-Term Memories neural network, Recurrent Neural Network, TensorFlow and Keras library are applied here. Those deep learning models and algorithms help to achieve overall 97.57% accuracy on arrhythmia prediction.

However, there is no research implemented in the mobile device by combining the two algorithms into one algorithm. This means that it is necessary to prove whether the MobileNet v2-BiLSTM algorithm can be implemented on the Mobile device. The algorithm proposed in this paper classified ECG data using MobileNet v2 and BiLSTM, and the results showed that MobileNet v2-BiLSTM could detect heart disease. In a further study, the authors will lighten the structure of BiLSTM and conduct experiments on whether this algorithm can be implemented on mobile devices.

The algorithm proposed in this study was designed for use in mobile devices. The proposed algorithm can analyze ECG signals in everyday life and check for heart disease. In addition, when the number of data is small, a sufficient amount of data can be secured by adding data using a matching pursuit. However, MobileNet V2-BiLSTM-based algorithms have not yet been implemented on mobile devices. This is because the deep learning algorithm has a complex structure and includes many parameters.

However, research is underway to implement and evaluate deep learning using mobile devices. Liu, j, et al analyzed the performance of training a deep learning

network on a mobile device. Deep learning used several things such as DenseNet, ResNet, VGG, and LSTM, and considered hardware performance when analyzing deep learning performance.

And Saadatnejad, S, et al conducted a study on the LSTM-RNN-based ECG classification algorithm [38]. The proposed algorithm is lightweight, and therefore, brings continuous monitoring with accurate LSTM-based ECG classification to wearable devices.

Considering these studies, the algorithm proposed in this study can be implemented on a mobile device. However, further research needs to be conducted to reduce the structure of the MobileNet V2-BiLSTM algorithm and to efficiently update parameters.

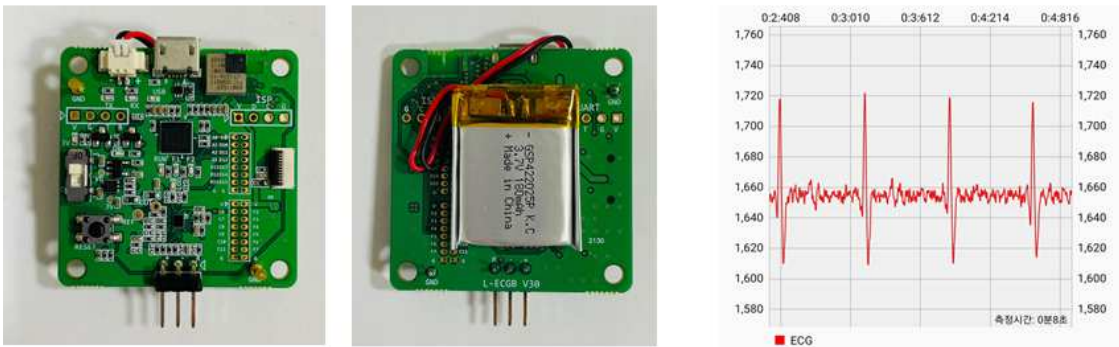


Figure 4.6. Bio-signal measurement module for arrhythmia detection

Figure 4.6 shows a bio-signal measurement module capable of measuring an electrocardiogram. The module uses a lithium-ion battery and weighs 5.32 grams. It also uses Bluetooth-based wireless communication.

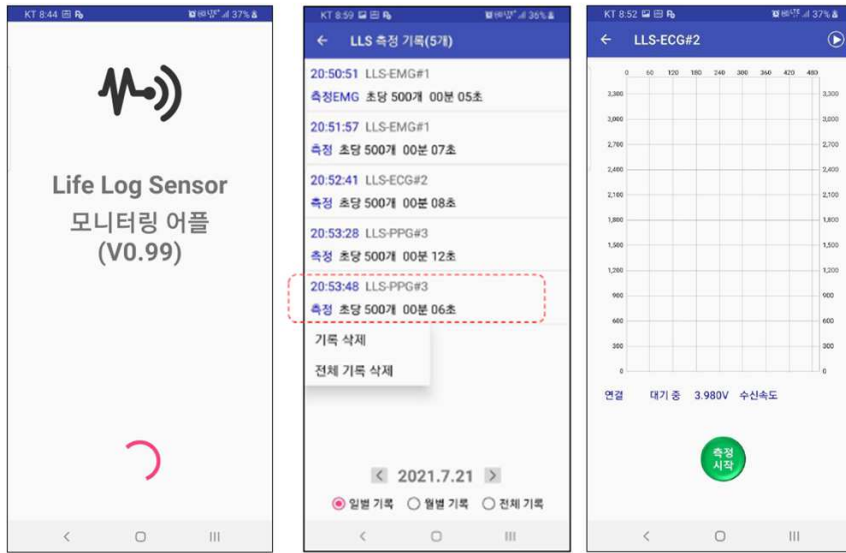


Figure 4.7. Bio-signal Monitoring application in mobile device

Figure 4.7 is an app representing a bio-signal measured from a user. Users can check their health using this app. The App helps users access ECG databases whenever they want, and ECG data is stored according to the date.

## IV. Conclusion

We proposed an artificial intelligence model for classifying arrhythmia using MobileNetV2-BiLSTM and a matching pursuit algorithm. The ECG data measured over a short period were augmented with sufficient quantities of data using the matching pursuit algorithm, and the MobileNetV2-BiLSTM-based arrhythmia diagnosis results exhibited an accuracy of 91.7%. The performance of the model was evaluated using the ROC curve, and the average AUC was 0.994, indicating that the performance of the classifier was excellent. The algorithm arbitrarily added ECG data to increase its accuracy. In this process, the matching pursuit algorithm was used, and a large number of data could be secured. The data augmentation method used in the present study can be applied to imbalanced datasets. If the dataset is imbalanced, an overfitting problem can occur, reducing the accuracy. If the matching pursuit algorithm can solve the imbalance problem, the proposed algorithm can classify data from various datasets in addition to the ECG datasets used in this study. Owing to the widespread use of portable devices, various applications of lightweight algorithms will be developed in the future. After further research, the proposed MobileNetV2-BiLSTM model is expected to be useful in various fields, such as healthcare and the Internet of Things, in addition to disease monitoring.

## Reference

- [1] Yıldırım, Ö.; Pławiak, P.; Tan, R.S.; Acharya, U.R. Arrhythmia detection using deep convolutional neural network with long duration ECG signals. *Comput. Biol. Med.* 2018, 102, 411–420.
- [2] Tuncer, T.; Dogan, S.; Pławiak, P.; Acharya, U.R. Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals. *Knowl. Based Syst.* 2019, 186, 104923.
- [3] Rocha, V.D.A.; do Carmo, J.C.; Nascimento, F.A.D.O. Weighted-cumulated S-EMG muscle fatigue estimator. *IEEE J. Biomed. Health Inform.* 2017, 22, 1854–1862.
- [4] Zhou, S.; AbdelWahab, A.; Sapp, J.L.; Sung, E.; Aronis, K.N.; Warren, J.W.; Chrispin, J. Assessment of an ECG-Based System for Localizing Ventricular Arrhythmias in Patients with Structural Heart Disease. *J. Am. Heart Assoc.* 2021, 10, e022217.
- [5] Aamir, K.M.; Ramzan, M.; Skinadar, S.; Khan, H.U.; Tariq, U.; Lee, H.; Khan, M.A. Automatic Heart Disease Detection by Classification of Ventricular Arrhythmias on ECG Using Machine Learning. *CMC-Comput. Mater. Contin.* 2022, 71, 17–33.
- [6] Ahmed, N.; Zhu, Y. Early detection of atrial fibrillation based on ECG signals. *Bioengineering* 2020, 7, 16.
- [7] A Report from the American Heart Association. Available online: <https://www.ahajournals.org/doi/10.1161/CIR.0000000000000950> (accessed on 2 March 2022).

- [8] Saboori, R.; Salehi, A.W.; Vaidya, P.; Gupta, G. Classification of Arrhythmia Using Machine Learning Techniques. In Innovations in Information and Communication Technologies (IICT-2020); Springer: Cham, Switzerland, 2021; pp. 445-452.
- [9] Faust, O.; Acharya, U.R. Automated classification of five arrhythmias and normal sinus rhythm based on RR interval signals. *Expert Syst. Appl.* 2021, 181, 115031.
- [10] Liu, S.; Shao, J.; Kong, T.; Malekian, R. ECG Arrhythmia classification using high order spectrum and 2D graph Fourier transform. *Appl. Sci.* 2020, 10, 4741.
- [11] Raut, N.V.; Deolekar, R.V. ECG Arrhythmia Classification using Fast Fourier Transform and Principal Component Analysis. *Int. J. Innov. Res. Technol.* 2021, 8, 786-791.
- [12] Sahoo, S.; Mohanty, M.; Sabut, S. Automated ECG beat classification using DWT and Hilbert transform-based PCA-SVM classifier. *Int. J. Biomed. Eng. Technol.* 2020, 32, 287-303.
- [13] Gupta, V.; Mittal, M. R-peak based Arrhythmia Detection using Hilbert Transform and Principal Component Analysis. In Proceedings of the 2018 3rd International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH), Ghaziabad, India, 1-2 November 2018; pp. 1-4.
- [14] Karunadas, C.P.; Mathew, C. Comparison of arrhythmia detection by conventional Holter and a novel ambulatory ECG system using patch and Android App, over 24 h period. *Indian Pacing Electrophysiol. J.* 2020, 20, 49-53.
- [15] Singh, V.; Tewary, S.; Sardana, V.; Sardana, H.K. Arrhythmia Detection-A Machine Learning based Comparative Analysis with MIT-BIH ECG Data. In

Proceedings of the 2019 IEEE 5th International Conference for Convergence in Technology (I2CT), Bombay, India, 29–31 March 2019.

[16] Yan, W.; Zhang, Z. Online Automatic Diagnosis System of Cardiac Arrhythmias Based on MIT-BIH ECG Database. *J. Healthc. Eng.* 2021, 2021, 1819112.

[17] Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A.; Chen, L.C. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, USA, 18–23 June 2018; pp. 4510–4520.

[18] Khan, A.H.; Hussain, M.; Malik, M.K. Cardiac disorder classification by electrocardiogram sensing using deep neural net-work. *Complexity* 2021, 2021, 5512243.

[19] Ahsan, M.M.; Nazim, R.; Siddique, Z.; Huebner, P. Detection of COVID-19 patients from CT scan and chest X-ray data using modified MobileNetV2 and LIME. *Healthcare* 2021, 9, 1099.

[20] Ahsan, M.M.; Siddique, Z. Machine learning-based heart disease diagnosis: A systematic literature review. *arXiv* 2021, arXiv:2112.06459.

[21] Wang, J.; Li, W. Atrial fibrillation detection and ECG classification based on CNN-BILSTM. *arXiv* 2020, arXiv:2011.06187.

[22] Luo, L.; Yang, Z.; Yang, P.; Zhang, Y.; Wang, L.; Lin, H.; Wang, J. An attention-based BiLSTM-CRF approach to document-level chemical named entity recognition. *Bioinformatics* 2018, 34, 1381–1388.

[23] Hernando-Ramiro, C.; Lovisolo, L.; Cruz-Roldán, F.; Blanco-Velasco, M. Matching Pursuit Decomposition on Electrocardiograms for Joint Compression and QRS Detection. *Circuits Syst. Signal Process.* 2019, 38, 2653–2676.

- [24] Sundarasekar, R.; Thanjaivadivel, M.; Manogaran, G.; Kumar, P.M.;Varatharajan, R.; Chilamkurti, N.; Hsu, C.H. Internet of things with maximal overlap discrete wavelet transform for remote health monitoring of abnormal ECG signals. *J. Med. Syst.* 2018, 42, 228.
- [25] Xu, X.; Liang, Y.; He, P.; Yang, J. Adaptive motion artifact reduction based on empirical wavelet transform and wavelet thresholding for the non-contact ECG monitoring systems. *Sensors* 2019, 19, 2916.
- [26] Dwivedi, A.K.; Ranjan, H.; Menon, A.; Periasamy, P. Noise reduction in ECG signal using combined ensemble empirical mode decomposition method with stationary wavelet transform. *Circuits Syst. Signal Process.* 2021, 40, 827-844.
- [27] Apandi, Z.F.M.; Ikeura, R.; Hayakawa, S. Arrhythmia detection using MIT-BIH dataset: A review. In *Proceedings of the 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA)*, Kuching, Malaysia, 15-17 August 2018; pp. 1-5.
- [28] Yan, W.; Zhang, Z. Online Automatic Diagnosis System of Cardiac Arrhythmias Based on MIT-BIH ECG Database. *J. Healthc. Eng.* 2021, 2021, 1819112.
- [29] Kuila, S.; Dhanda, N.; Joardar, S. Feature Extraction and Classification of MIT-BIH Arrhythmia Database. In *Proceedings of the 2nd International Conference on Communication, Devices and Computing*, Haldia, India , 14-15 March 2019; Springer: Singapore, 2020; pp. 417-427.
- [30] Ribeiro, H.D.M.; Arnold, A.; Howard, J.P.; Shun-Shin, M.J.; Zhang, Y.; Francis, D.P.; Zolgharni, M. ECG-based real-time ar-rhythmia monitoring using quantized deep neural networks: A feasibility study. *Comput. Biol. Med.* 2022, 143, 105249.



- [31] Naz, M.; Shah, J.H.; Khan, M.A.; Sharif, M.; Raza, M.; Damaševičius, R. From ECG signals to images: A transformation based approach for deep learning. *PeerJ Comput. Sci.* 2021, 7, e386.
- [32] Cai, J.; Sun, W.; Guan, J.; You, I. Multi-ECGNet for ECG arrhythmia multi-label classification. *IEEE Access* 2020, 8, 110848–110858.
- [33] Park, J.; Kim, J.K.; Jung, S.; Gil, Y.; Choi, J.I.; Son, H.S. ECG-signal multi-classification model based on squeeze-and-excitation residual neural networks. *Appl. Sci.* 2020, 10, 6495.
- [34] Lee, H.; Yoon, T.; Yeo, C.; Oh, H.; Ji, Y.; Sim, S.; Kang, D. Cardiac Arrhythmia Classification Based on One-Dimensional Morphological Features. *Appl. Sci.* 2021, 11, 9460.
- [35] Understanding AUC-ROC Curve. Available online: <https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5> (accessed on 20 February 2022).
- [36] Rincon, J. A.; Guerra-Ojeda, S.; Carrascosa, C.; Julian, V. An IoT and fog computing-based monitoring system for cardiovascular patients with automatic ECG classification using deep neural networks. *Sensors*, 2020, 20(24), 7353.
- [37] Ahsanuzzaman, S. M.; Ahmed, T.; Rahman, M. A. Low cost, portable ECG monitoring and alarming system based on deep learning. In 2020 IEEE Region 10 Symposium (TENSYP), 2020, 316–319.
- [38] Saadatnejad, S.; Oveisi, M.; Hashemi, M. LSTM-based ECG classification for continuous monitoring on personal wearable devices. *IEEE journal of biomedical and health informatics*, 2019, 24(2), 515–523.

## List of Publications

### Paper

- 1) S.H Shin, M.G Kang, G. Zhang, J.H Jung, and Youn Tae Kim, "Lightweight Ensemble Network for Detecting Heart Disease Using ECG Signals" Applied sciences 12(7), 3291 (2022)
- 2) S.H Shin, M.G Kang, J.H. Jung and Y. T. Kim, "Development of Miniaturized Wearable Wristband Type Surface EMG Measurement System for Biometric Authentication, Electronics", 10(8) 923-836 (2021)
- 3) S.H Shin, J.H. Jung and Y. T. Kim, "Federated Learning based Arrhythmia detection algorithm for mobile healthcare", Will be submit to IEEE access
- 4) J.H Jung, S.H Shin, M. Li, YT Kim, "Fabrication of Implantable Capsule-Type Channel Sounders for the High-Accuracy Measurement of the Signal Loss of Out-Body to In-Body Channels." Electronics 10.23 (2021): 2895
- 5) J.H Jung, S.H Shin, M. Li, YT Kim. "Telemetry Transmission to Support Bidirectional Communication for Capsule Endoscope Using Human Body Communication." IEEE Microwave and Wireless Components Letters 31.7 (2021): 905-908
- 6) M.G Kang, S.H Shin, J.H jung and Youn Tae Kim "Classification of mental stress using cnn-lstm algorithms with electrocardiogram signals." Journal of Healthcare Engineering 2021 (2021).
- 7) M.G Kang, S.H Shin, Gengjia Zhang, J.H jung and Youn Tae Kim. "Mental Stress Classification Based on a Support Vector Machine and Naive Bayes

Using Electrocardiogram Signals." Sensors 21.23 (2021): 7916.

8) K.H Kang, M.G Kang, S.H Shin J.H. Jung\* and M. Li, "Estimating Physical Activity Energy Expenditure Using an Ensemble Model-Based Patch-Type Sensor Module", Electronics, 10(7) 861-872 (2021)

9) J.H. Jung, S.H Shin, M.G Kang, K.H Kang and Y. T. Kim, "Development of wearable wireless electrocardiogram detection system using Bluetooth low energy", Electronics, 10(5) 608-618 (2021)

10) K.H Kang, S.H Shin, J.H. Jung and Y. T. Kim, "Estimation of a physical activity energy expenditure with a patch-type sensor module using artificial neural network, Concurrency and Computation: Practice and Experience", 33(2), e5455 (2021)

11) J.H Jung, S.H Shin and Y. T. Kim, "Dry Electrode Made from Carbon Nanotubes for Continuous Recording of Bio-Signals, Microelectronic Engineering", 203-204(2019)

12) J.H Jung, J. H Lee, S.H Shin and Y. T. Kim, "Development of a Telemetric, Miniaturized Electrochemical Amperometric Analyzer, Sebsirs", 17(10), 2416-2424 (2017)

## List of Publications

### Conference

- 1) "Development of Algorithm to Predict Arrhythmias based on Ensemble Network using Electrocardiogram", S.H Shin, M.G Kang, G. Zhang, J.H Jung, M. Li and Y. T. Kim, CSCI2021
- 2) "Arrhythmia Detection Algorithm using GoogLeNet and Generative Adversarial Network with Lifelog Signals" S.H Shin, J.H Jung, M.G Kang, Y. T. Kim, EECS 2020
- 3) "Electromyogram-based Algorithm Using Bagged Trees for Biometric Person Authentication and Motion Recognition" S.H Shin, J.H Jung, M.G Kang Kyeung Ho Kang and Y. T. Kim, ICCE 2020
- 4) "Multi Bio-Signal Based Algorithm Using EMD and FFT for Stress Analysis" M.G Kang, J.H Jung, S.H Shin, Kyeung Ho Kang and Y. T. Kim, ICCE 2020
- 5) "Stress Classification Using K-means Clustering and Heart Rate Variability from Electrocardiogram" M.G Kang, S.H Shin, J.H Jung and Y. T. Kim, EECS 2020
- 6) "Development of semi-supervised learning-based blood pressure estimation system" J.H Jung, S.H Shin, M.G Kang Kyeung Ho Kang and Y. T. Kim, CSCI 2019
- 7) "A Study on EMG Signal Acquisition Modules and Artificial Neural Networks for Personal Authentication" S.H Shin, J.H Jung, M.G Kang and Y. T. Kim, CSCI 2018

- 8) "A Study of Wireless system for ECG healthcare monitoring" J.H Jung, S.H Shin, M.G Kang and Y. T. Kim, CSCI 2018
- 9) "A study of an EMG-based authentication algorithm using an Artificial Neural Network" S.H Shin, J.H Jung and Y. T. Kim, IEEE sensors 2017
- 10) "Gesture-based controller using wrist electromyography and a neural network classifier" S.H Shin, Seokeun Park, J.H Jung and Y. T. Kim, Biomedical Engineering and Sciences BIOENG'16
- 11) "Flexible Dry Electrodes Made from CNT/Textile Composite for ECG Sensor" J.H Jung, S.H Shin and Y. T. Kim, Biomedical Engineering and Sciences BIOENG'16

## List of Publications

### Patent

- 1) “심전도 측정 안드로이드용 어플리케이션”, 김윤태, 정재효, 신시호, (Dec 07,2016, C-2016-031277)
- 2) Y T Kim, JH Jung, SH Shin “wearable device for measuring edema index and method of measuring edema index using same“ KR Application Number: 10-2016-0106397; US Application Number: 15/364,326
- 3) “부종 지수의 측정을 위한 웨어러블 디바이스 및 이를 이용한 부종 지수 측정 방법”, 김윤태, 정재효, 신시호 (Aug 22. 2016, KOR, 10-2016-0106397)
- 4) "진공 흡착을 이용한 CNT 혼합 전극", 김윤태, 정재효, 신시호 (Oct 19. 2017, KOR 10-2017-0129839)
- 5) Y T Kim, JH Jung, MG Kang, SH Shin “Stress classification device and method”, KR Application Number: 10-2020-0155959
- 6) "자전거 운전자의 생체 신호 모니터링 장치, 방법 및 컴퓨터로 독출 가능한 기록 매체", 김윤태, 정재효, 신시호 (Oct 19. 2017, 0129840)
- 7) "근전도 신호 기반 사용자 인증 장치 및 인증 방법", 김윤태, 정재효, 신시호, 강민구 (Oct 22. 2019, 10-2019-0131278)
- 8) "소음의 영향에 따른 심전도 신호를 이용한 스트레스 지수 측정 장치 및 방법", 김윤태, 정재효, 신시호, 강민구
- 9) "무선 통신을 이용한 심전도 측정 장치, 방법 및 컴퓨터로 독출 가능한 기록 매체",

김윤태, 정재효, 이지훈, 신시호(Feb 11. 2020, 10-2020-0014477 )

10) Y T Kim, JH Jung, MG Kang, SH Shin “Personal authentication system based on EMG signal and Method of Operating The same”, KR Application Number: 10-2019-0131278; US Application Number: 16/870,251

## **ABSTRACT**

# **Development of Lightweight Ensemble Network for Detecting Heart Disease Using ECG Signals**

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Heart disease should be treated quickly when symptoms appear. Machine-learning methods for detecting heart disease require desktop computers, an obstacle that can have fatal consequences for patients who must check their health periodically. In this work, we propose Federated learning and MobileNetV2-BiLSTM-based ensemble algorithms for arrhythmia diagnosis that can operate easily and quickly in a mobile environment. The electrocardiogram (ECG) signal measured over a short period of time was augmented using the matching pursuit algorithm to achieve a high accuracy. The arrhythmia data were classified through an ensemble classifier combining MobileNetV2 and BiLSTM. By classifying the data using this algorithm, an accuracy of 91.7% was achieved. The performance of the algorithm was evaluated using a confusion matrix and a receiver operating characteristic curve. The sensitivity, specificity, precision, and F1 score were 0.92, 0.91, 0.92, and 0.92, respectively. Because the proposed algorithm does not require long-term ECG signal measurement, it facilitates health management for busy people. Moreover, parameters are exchanged when learning data, enhancing



the security of the system. In addition, owing to the lightweight deep-learning model, the proposed algorithm can be applied to mobile healthcare, object detection, text recognition, and authentication.