IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 5 March 2024, accepted 19 March 2024, date of publication 25 March 2024, date of current version 29 March 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3380892*

RESEARCH ARTICLE

# An Automated Cardiac Arrhythmia Classification Network for 45 Arrhythmia Classes Using 12-Lead Electrocardiogram

**HO KEUN KIM, (Graduate Student Member, IEEE), AND MYUNG HOON SUNWOO, (Life Fellow, IEEE)**

Department of Electrical and Computer Engineering, Ajou University, Suwon 16499, South Korea

Corresponding author: Myung Hoon Sunwoo (sunwoo@ajou.ac.kr)

This work was supported in part by the Ministry of Science and Information and Communications Technology (MSIT), South Korea, through the Information Technology Research Center (ITRC) Support Program, Supervised by the Institute for Information and Communications Technology Planning and Evaluation (IITP), under Grant IITP-2023-2020-0-01461; and in part by the National Research and Development Program through the National Research Foundation of Korea (NRF) funded by the MSIT under Grant NRF-2021R1A2C2010228.

**ABSTRACT** Electrocardiogram is a non-invasive, inexpensive, and widely used diagnostic tool for arrhythmia diagnosis in clinics. Deep learning techniques have shown great promise in electrocardiogram signal analysis, enabling automatic and accurate detection of various cardiac arrhythmia. This paper proposes an automated multi-label cardiac arrhythmia classification network based on a convolutional neural network. The network aims to detect and classify 45 different cardiac arrhythmia classes using 12-lead electrocardiogram data. Unlike previous studies, our approach incorporates both the residual structure and channel attention mechanism. Thus, we developed two key schemes to improve classification performance: the Global Channel Attention Block and the Short Residual Block. The Global Channel Attention Block incorporates dilated convolutions to preserve overall features. It focuses on the important characteristics of each arrhythmia class from the original electrocardiogram data during the training process. The Short Residual Block employs a residual structure to enhance classification accuracy. The network's performance is evaluated using a large-scale 12-lead electrocardiogram database for arrhythmia study on PhysioNet and the 2018 China Physiological Signal Challenge dataset. In particular, the proposed classification network shows the highest scores in average precision, recall, F1 score, area under the receiver operating characteristic, and accuracy compared to existing convolutional neural network-based arrhythmia classification networks in a large-scale 12-lead electrocardiogram database for arrhythmia study on PhysioNet.

**INDEX TERMS** 12-lead electrocardiogram, deep learning, convolutional neural network, multi-label classification, cardiac arrhythmia classification.

## I. INTRODUCTION

According to the World Health Organization (WHO), heart diseases cause millions of deaths globally [1]. In such diseases, Electrocardiogram (ECG) is a non-invasive, inexpensive, and widely used diagnostic tool for arrhythmia diagnosis in clinics. It records the heart's electrical activities over time through electrodes attached to the skin surface. As shown in Fig. 1, a standard 12-lead ECG can be acquired from ten skin surface sensors, including four limb leads (right arm (RA), left arm (LA), right leg (RL), and left leg (LL)) and six chest leads (VI, V2, V3, V4, V5, and V6).

An ECG is a graph depicting voltage with respect to time that reflects the electrical activities of cardiac muscle depolarization followed by repolarization during each heartbeat [2]. As shown in Fig. 2, the ECG graph of a normal

The associate editor coordinating the review of this manuscript and approving it for publication was Kathiravan Srinivasan.

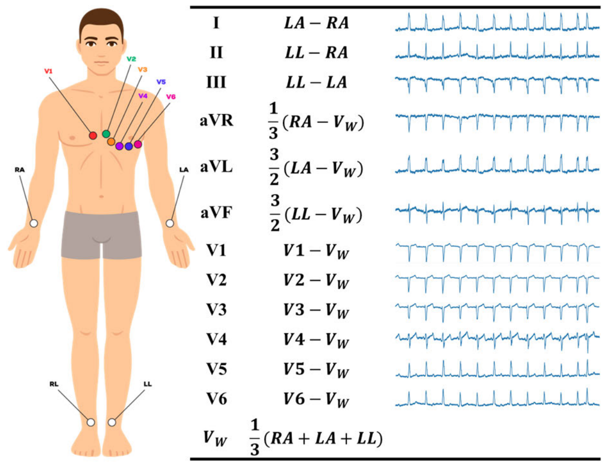


**FIGURE 1.** Illustration for 12-lead ECG system.

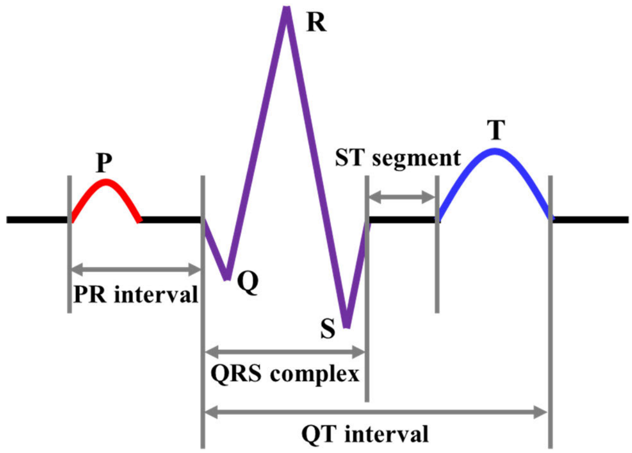


**FIGURE 2.** Fiducial points and features of ECG signal.

beat consists of a sequence of waves: a P-wave presenting the atrial depolarization process, a QRS complex denoting the ventricular depolarization process, and a T-wave representing the ventricular repolarization. Other signal portions include the PR, ST, and QT intervals. Automatic arrhythmia detection is an important topic in the field of cardiology.

Recently, an automated interpretation of ECG is of great significance for early prevention and diagnosis of cardiac arrhythmia [3]. Specifically, many approaches have been presented for cardiac arrhythmia detection using single-lead ECG [4], [5], [6], but it is insufficient for precisely diagnosing various kinds of heart diseases using only single-lead ECG. Therefore, 12-lead ECG, which is the standard clinical ECG test has attracted increasing interest from researchers.

Over the past decade, a large number of automatic arrhythmia detection algorithms using machine learning (ML) and classifiers have been introduced [7], [8], [9], [10], [11], [12]. Although these researches improve the accuracy of cardiac arrhythmia classification, they still have some common defects [13]. First, they must rely on experts to design and extract the characteristics of ECG signals, other potential information in the original signal is neglected. Second, the artificial definition of different disease characteristics may be slightly different, therefore, the generalization ability of the model is restricted.

Deep learning techniques have shown great promise in ECG signal analysis, enabling automatic and accurate detection of various cardiac arrhythmia [13], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28] and [37], [38], [39], [40]. Deep neural network (DNN) realizes the effective combination of feature extraction and cardiac arrhythmia classification through end-to-end learning. However, deep learning-based cardiac arrhythmia classification still has some limitations. First, the existing studies [13], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [37], [38], [39], and [40] have either utilized many publicly available datasets or collected their own datasets using individual approaches. However, there is still a lack of studies that classify various arrhythmia classes. Specifically, previous studies [13], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [37], [38], [39], and [40] focused on classifying a single class or only around ten arrhythmia classes. According to [18], more than 60 types of arrhythmia classes exist in various manifestations. In particular, a previous study [37] attempted to classify 26 types of arrhythmia classes, but it is still insufficient. Therefore, automated cardiac arrhythmia classification using deep learning is essential to detect and classify many arrhythmia classes. Second, the CNN-based cardiac arrhythmia classification using 12-lead ECG data mainly depends on residual structures in other studies. To classify multi-label arrhythmia classes, it is essential to incorporate both residual structure and channel attention mechanism, such as SENet [30]. P. Nejedly et al. [37] applied the multi-head-attention mechanism. However, channel attention mechanism such as SENet [30] is suitable for processing ECG signals. These structures allow the model to focus on important features within ECG signals during the learning process.

This paper proposes automated multi-label cardiac arrhythmia classification based on convolution neural network (CNN) using 12-lead ECG data. The proposed network can detect and classify 45 cardiac arrhythmia classes using the PhysioNet's a large-scale 12-lead electrocardiogram database [18], which contains 51 arrhythmia classes. Unlike previous studies, our approach incorporates both the residual structure and channel attention mechanism. In other words, we introduce short residual block (SRB) and global channel attention block (GCAB) to focus on the important characteristics of each arrhythmia class from the original 12-lead ECG data during the training process.

The main contributions are summarized as follows:

1) We developed an automated multi-label cardiac arrhythmia classification network, which detects and classifies 45 cardiac arrhythmia classes using 12-lead ECG data. Additionally, using convolution kernels with different receptive fields, our proposed network outperforms the other CNN-based cardiac arrhythmia classification networks.

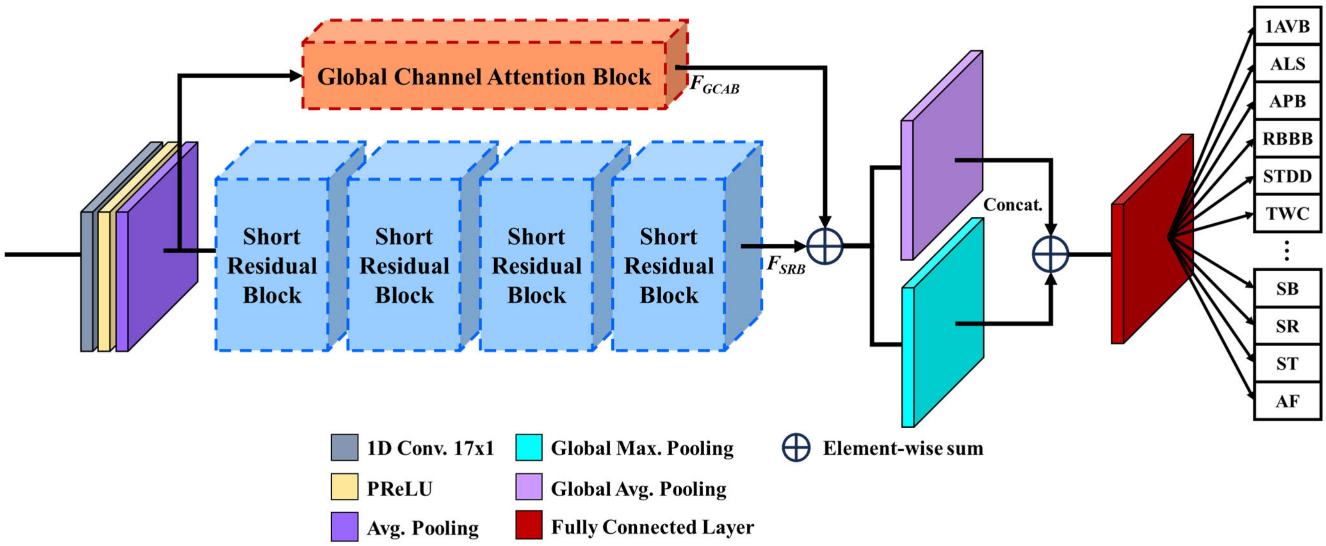


**FIGURE 3.** The proposed automated multi-label cardiac arrhythmia classification network architecture.

2) We propose SRB and GCAB to focus on the main characteristics of each arrhythmia class from the original 12-lead ECG data during the training process. By modifying the channel attention block [29], our proposed network can improve detection and classification performance. By incorporating this proposed channel attention structure and residual structure into our network, we can detect and classify 45 cardiac arrhythmia classes.
3) We evaluate the proposed network for cardiac arrhythmia classification on a publicly available ECG dataset (a large-scale 12-lead electrocardiogram database for arrhythmia study [18]) and compare it with other state-of-the-art CNN-based cardiac arrhythmia classification networks. Furthermore, we performed additional experiments using another public ECG dataset, which is CPSC 2018 [16]. The experimental results demonstrate the classification ability of our proposed network.

The remainder of this paper is structured as follows. Section II presents the related works on traditional methods, recurrent neural network (RNN) based methods, and existing CNN-based methods. Section III describes the proposed automated multi-label cardiac arrhythmia classification network in detail. Section IV describes the datasets and parameters used for training and testing and presents experiment results. Section V discusses the limitations of our work and previous works. In addition, we discuss how future research should proceed. Finally, we summarize and conclude the paper in Section VI.

## II. RELATED WORKS

### A. TRADITIONAL METHODS USING MACHINE LEARNING AND CLASSIFIER

The existing methods [7], [8], [9], [10], [11], [12] consist of machine learning algorithms and classifiers. Homaeinezhad et al. [7] presented a heartbeat recognition algorithm using the support vector machine (SVM). The existing methods [8] based on machine learning (ML) algorithms are of two stages; these methods require experts to engineer useful features or extract features using signal processing techniques and then use these features to build ML classifiers [8]. Detta et al. [9] developed a feature-oriented method with a two-layer cascaded binary classifier. They performed best in the 2017 PhysioNet/CinC Challenge for atrial fibrillation classification from single-lead ECGs. On the other hand, feature extraction methods exist in the existing methods [10], [11], [12]. The first and most important step is feature extraction, which needs to be manually designed and extracted from the raw signal. Early approaches mainly rely on classical waveform features, such as amplitudes, Hermite coefficients [10], morphological features [11], heartbeat interval features [12], etc.

### B. RECURRENT NEURAL NETWORK-BASED METHODS

RNN can be one of the classification methods to classify cardiac arrhythmia. Zhang et al. [41] proposed a multi-lead-branch fusion network for multi-label arrhythmia classification based on the bidirectional gated recurrent unit (BiGRU). They integrated multi-loss optimization to jointly learning the diversity and integrity of 12-lead ECG. Additionally, their proposed network classifies 23 types of cardiac arrhythmia classes. Xie et al. [42] presented multi-label 12-lead ECG classification based on bidirectional long short-term memory (Bi-LSTM). Zhang et al. [41] and Xie et al. [42] attempted to classify 23 and 27 cardiac arrhythmia classes, respectively. However, it is still insufficient to address numerous types of cardiac arrhythmia classes. Furthermore, He et al. [43] and Yao *et at.* [44] proposed LSTM combined with CNN architectures to classify cardiac arrhythmias.

### C. CONVOLUTIONAL NEURAL NETWORK-BASED METHODS

Recently, CNN has achieved remarkable performance in cardiac arrhythmia classification. Hannun et al. [19] presented an end-to-end DNN to detect and classify arrhythmia using 91,232 single-lead ECGs from 53,549 patients. They showed superior performance than cardiologists for diagnosing twelve rhythm classes. Zhang et al. [20] presented a DNN based on residual structure for automatic diagnosis of 12-lead ECG. Their proposed DNN could classify nine rhythm classes using the CPSC 2018 dataset and achieved superior performance than four ML methods on average F1 score. Duan et al. [21] proposed an end-to-end DNN structure based on SENet [30] to classify cardiac abnormalities of 12-lead ECG. Riberio et al. [22] also presented an automatic diagnosis of the 12-lead ECG using DNN. They collected a dataset consisting of 2,322,513 ECG records from 1,676,384 different patients of 800 counties in Minas Gerais/Brazil from the Telehealth Network of Minas Gerais (TNMG) [31]. Their proposed network could detect and classify six arrhythmia classes from 12-lead ECG. Park et al. [23] presented CNN-based ST-elevation myocardial infarction (STEMI) detection from 12-lead ECG. They co-worked at Seoul National University Bundang Hospital (SNUBH) and trained 265 ECG records using VGGNet [32] and ResNet [33] for STEMI detection.

## III. PROPOSED METHOD

This paper proposes an automated multi-label cardiac arrhythmia classification network using CNN, which can detect and classify 45 cardiac arrhythmia classes. To enhance the performance of the cardiac arrhythmia classification, we propose GCAB and SRB. We describe the details of the whole procedure below.

### A. THE PROPOSED CLASSIFICATION NETWORK ARCHITECTURE TO CLASSIFY 45 CARDIAC ARRHYTHMIA CLASSES

Generally, 2D CNN is used for image processing. However, unlike image processing, ECG signals require 1D CNN. Hence, all computational processes used in the proposed classification network were implemented using 1D CNN [34]. The proposed classification network takes 12-lead raw ECG signals $x \in \mathbb{R}^{\{nsamples \times 12\}}$ ($nsamples$ is 5,000) as input and outputs a multi-label classification result $y \in \mathbb{R}^{1\times 45}$.

Fig. 3 illustrates the proposed automated multi-label cardiac arrhythmia classification network structure, consisting of an initial feature extraction block, one GCAB to focus on important features from the 12-lead ECG signals, four SRBs, and a pooling layer to make predictions. Within the initial feature extraction block, we employ one convolution layer for extracting features, one parametric rectified linear unit (PReLU) activation layer, and one average pooling layer. We focused on extracting meaningful features in the initial stages to improve classification performance.

**TABLE 1. Architecture of the proposed 12-lead ECG classification network.**

| Layer | Layer Details | | Output |
|---|---|---|---|
| Initial Block | [Conv_17_64_1_1] + BN + ReLU | | 12x64x5000 |
| | Avg. Pooling, 1x1 | | 12x64x5000 |
| Short Residual Block #1 | [Conv_13_64_1_1] + BN + ReLU | | 12x64x5000 |
| | Dropout, 0.5 | | 12x64x5000 |
| | [Conv_13_64_1_1] + BN + ReLU | | 12x64x5000 |
| Short Residual Block #2 | [Conv_13_128_2_1] + BN + ReLU | | 12x128x2500 |
| | Dropout, 0.5 | | 12x128x2500 |
| | [Conv_13_128_1_1] + BN + ReLU | | 12x128x2500 |
| Short Residual Block #3 | [Conv_13_256_2_1] + BN + ReLU | | 12x256x1250 |
| | Dropout, 0.5 | | 12x256x1250 |
| | [Conv_13_256_1_1] + BN + ReLU | | 12x256x1250 |
| Short Residual Block #4 | [Conv_13_512_2_1] + BN + ReLU | | 12x512x625 |
| | Dropout, 0.5 | | 12x512x625 |
| | [Conv_13_512_1_1] + BN + ReLU | | 12x512x625 |
| Global Channel Attention Block | [Conv_17_512_8_1] | | 12x512x625 |
| | Avg. Pooling, 1x1 | Max. Pooling, 1x1 | 12x512x625 |
| | [Conv_3_32_1_2] + ReLU | [Conv_3_32_1_2] + ReLU | 12x32x625 |
| | [Conv_3_512_1_2] | [Conv_3_512_1_2] | 12x512x625 |
| | Sigmoid Function | | 12x512x625 |
| | Dropout, 0.3 | | 12x512x625 |
| | PReLU | | 12x512x625 |
| | Dropout, 0.3 | | 12x512x625 |

**Note:** The 1D convolutional parameters are denoted as "Conv_(kernel size)_(number of filters)_(stride)_(dilation rate)".

Consequently, we opted for the trainable activation function PReLU, as shown in Eq. (1).

$$\mathrm{PReLU}(x) = \begin{cases} x, & \text{if } x \geq 0 \\ \alpha x, & \text{otherwise} \end{cases} \tag{1}$$

Unlike previously known networks [13], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [37], [38], [39], [40], the proposed classification network classifies 45 different cardiac arrhythmia classes. Therefore, different kernel sizes were applied to each block to improve classification performance. The kernel sizes and other variables for each block are summarized in Table 1. Following the initial stages, the features $F_{GCAB}$ and $F_{SRB}$ can be obtained through the GCAB and SRB, respectively, and then they are combined through element-wise sum, as shown in Eq. (2).

$$z = F_{GCAB} \oplus F_{SRB} \tag{2}$$

The feature map $z$ obtained by GCAB and SRB adopts global max pooling (GMP) and global average pooling (GAP) layers as Eq. (3), and then followed by a concatenation of the results of these two operations. Finally, after a fully connected (FC) layer, predictions for the 45 multi-label arrhythmias are generated. The generated $z$ is used as input data of the GMP and GAP and can be expressed as follows:

$$y = f_{FC}[Concat.(f_{GMP}(z), f_{GAP}(z))] \tag{3}$$

where Concat. denotes concatenated sum. As a result, the proposed automated multi-label cardiac arrhythmia classification network could achieve higher performance compared to other existing networks [19], [20], [21], and [23]. Detailed explanations regarding the experimental results are provided in Section IV.

As mentioned earlier, we focused on extracting feature maps in the initial stages. Moreover, we proposed GCAB, which additionally extracts the significant characteristics of each arrhythmia class from the features delivered in the initial stage. The proposed GCAB is detailed in Section III-B. In addition, the kernel sizes and other variables for GCAB are introduced in Table 1.

As depicted in Fig. 3, the proposed network comprises 4 SRBs. Generally, the residual structure is widely used in 2D CNN and has demonstrated excellent performance, particularly in image classification tasks. Despite cardiac arrhythmia classification using ECG signals employing 1D convolution instead of 2D convolution-like images, the residual structure still performs well in the context of 1D convolution. Consequently, we propose the SRB utilizing 1D convolution, and its detailed explanation is covered in Section III-C. In addition, the kernel sizes and other variables for SRB are also summarized in Table 1.

### B. GLOBAL CHANNEL ATTENTION BLOCK (GCAB)

Applying only the residual structure can lead to high performance in many arrhythmia classification networks [19], [20], [21], [22], [23]. However, as the number of arrhythmia classes increases, the application of other methods, such as the attention mechanism as well as the residual structure, is required to achieve high performance. We applied an attention mechanism to preserve and convey the main characteristics of each arrhythmia class as much as possible in the initial stages.

Like the residual structure, the attention method was initially introduced for image classification [29]. However, we modified the existing attention method for one-dimensional operations such as ECG signals. In other words, we propose the GCAB for multi-label 12-lead ECG classification.

Fig. 4 illustrates the structure of the proposed GCAB. We employed the dilated convolution technique to preserve and capture overall features within the attention block. The dilated convolution expands the receptive field size, making it possible to extract meaningful information from features obtained through the average pooling (AP) and max pooling (MP) layer in GCAB. Mathematically, for an input sequence $x \in \mathbb{R}^T$ and a convolutional kernel $w \in \mathbb{R}^K$, the 1D-dilated causal convolution operation $G$ on element $n$ of the sequence is defined as:

$$G[n] = \sum_{i=0}^{K-1} w[i] \cdot x[n - d \cdot i] \tag{4}$$

where $d$ is the dilation factor, $T$ is the sequence length, $K$ is the filter size, and $(n - d \cdot i)$ accounts for the direction of the past samples. Eq. (4) can be interpreted as the convolution of input $x$ and a filter $w$ with a dilation factor $d$. The dilated filter is obtained by introducing holes between the kernel elements of $w$ based on $d$. Furthermore, if $d = 0$, Eq. (4) becomes a standard 1D convolution operation. First, as shown in Eq. (5) and (6), the input sequence $x$ undergoes a convolution operation, passing through both an AP and an MP layer.

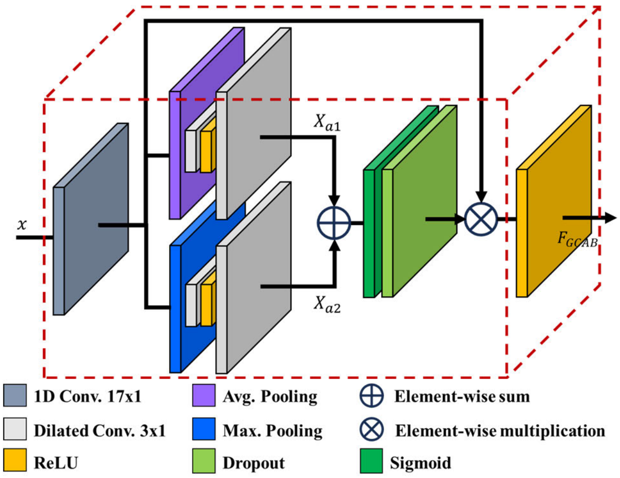


**FIGURE 4.** The proposed global channel attention block.

$$X_{a1} = G_{d=2}(f_{AP}(G_{d=0}(x))) \tag{5}$$
$$X_{a2} = G_{d=2}(f_{MP}(G_{d=0}(x))) \tag{6}$$

Secondly, each feature map, represented as $X_{a1}$ and $X_{a2}$ is added through an element-wise sum and then activated through a sigmoid activation function. Finally, by performing element-wise multiplication as shown in Eq. (7), followed by a ReLU activation layer, the final result $F_{GCAB}$ is obtained. To prevent overfitting during the learning process of the proposed network, we applied the dropout technique [35] to the proposed GCAB. Additionally, we defined the kernel size of the 1D convolution layer as 17 and applied the kernel size of the dilated convolution layer as 3.

### C. SHORT RESIDUAL BLOCK (SRB)

The initial proposal of the residual structure was in ResNet [32]. ResNet exhibited excellent performance in the 2D domain of image classification and demonstrated good results in the 1D domain of cardiac arrhythmia classification [19], [20], [21], [22], [23]. Unlike 2D CNN, input sequences are less complex in 1D CNN, which can lead to overfitting during the learning process. Additionally, using larger kernel sizes in convolution operations can significantly assist in extracting overall features from input data. Considering these factors, unlike conventional residual structures, the proposed SRB incorporates a dropout layer to mitigate overfitting [35].

Moreover, the kernel size is defined as 13. As shown in Fig. 5, the proposed SRB consists of two convolutional layers, two batch normalizations, two ReLU activation functions, and a dropout layer. The proposed SRB can be expressed as follows:

$$F_{SRB} = G_{d=0}(\mathrm{Dropout}(G_{d=0}(x))) \oplus x \tag{7}$$

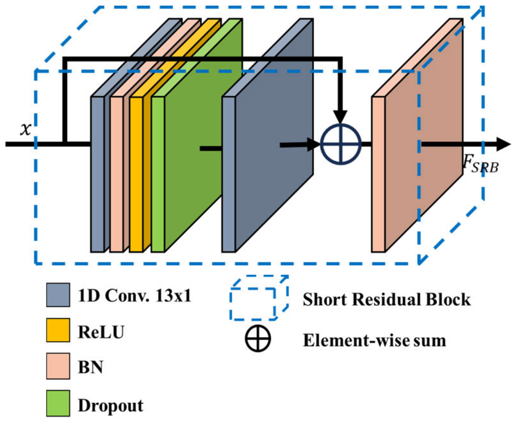


**FIGURE 5.** The proposed short residual block.

Unlike the GCAB described earlier, SRB does not incorporate dilated convolutions to focus on more specific features during training. It also has a higher risk of overfitting than the GCAB because the proposed classification network uses four SRBs. Consequently, we defined the dropout rate as 0.5 to avoid overfitting in SRBs.

## IV. IMPLEMENTATION RESULTS

In this section, implementation details and experimental results are given. In addition, it analyzes the performance of the proposed automated multi-label cardiac arrhythmia classification network by comparing it with existing CNN-based cardiac arrhythmia classification networks. We choose two 12-lead ECG datasets for validating the proposed automated multi-label cardiac arrhythmia classification network. In addition, we select SENet-34 [30] and ResNet-34 [32] as baseline networks to compare with our proposed network.

### A. DATASETS DESCRIPTION

1) A large-scale 12-lead ECG database for arrhythmia study [18]: This multi-label dataset was from the PhysioNet open databases. This database comprises 45,152 ECG data from the Shaoxing People's Hospital and Ningbo First Hospital. The ECG records are sampled at 500 Hz, and the signal length of the data is 10 seconds. We utilized 10 seconds of data for both our CNN training and testing. There are 51 classes with various distinct manifestations, such as sinus bradycardia (SB), atrial tachycardia (AT), premature ventricular contraction (PVC), and other irregular rhythms with missing or distorted wave segments and intervals. The most common and pernicious arrhythmia type is atrial fibrillation (AFIB). It is associated with a significant increase in the risk of severe cardiac dysfunction and stroke. We designed a classification network to predict and classify arrhythmias for a total of 45 classes, excluding the six classes with less than ten data samples such as atrial bigeminy (ABI), fragmented QRS wave (FQRS), junctional premature beat (JPT), ventricular bigeminy (VB), ventricular escape trigeminy (VET), and sinus atrium to atrial wandering rhythm (SAAWR) among the 51 classes. Finally, Table 2 shows the details of the data.

**TABLE 2.** Data details for a large-scale 12-lead ECG database for arrhythmia study.

| Arrhythmia Class | Num. of Cases | Male | Avg. Age | Signal Length (sec.) |
|---|---|---|---|---|
| 1AVB | 1,140 | 821 | 69.37 | 10.00 |
| 2AVB | 66 | 48 | 72.71 | 10.00 |
| 2AVB1 | 31 | 22 | 67.10 | 10.00 |
| 3AVB | 76 | 52 | 70.96 | 10.00 |
| ALS | 1,545 | 1,153 | 69.20 | 10.00 |
| APB | 1,312 | 805 | 71.54 | 10.00 |
| AQW | 1,063 | 791 | 70.04 | 10.00 |
| ARS | 853 | 462 | 54.98 | 10.00 |
| AVB | 244 | 143 | 70.40 | 10.00 |
| CCR | 162 | 60 | 62.78 | 10.00 |
| CR | 76 | 52 | 65.07 | 10.00 |
| ERV | 366 | 338 | 51.75 | 10.00 |
| IVB | 771 | 490 | 70.08 | 10.00 |
| JEB | 75 | 46 | 69.53 | 10.00 |
| LFBBB | 240 | 160 | 72.20 | 10.00 |
| LVH | 647 | 363 | 71.58 | 10.00 |
| LVQRSAL | 1,043 | 521 | 66.13 | 10.00 |
| MISW | 123 | 91 | 64.42 | 10.00 |
| PRIE | 52 | 41 | 66.71 | 10.00 |
| PWC | 142 | 96 | 63.40 | 10.00 |
| QTIE | 394 | 212 | 69.98 | 10.00 |
| RAH | 36 | 22 | 56.50 | 10.00 |
| RBBB | 649 | 448 | 71.12 | 10.00 |
| RVH | 110 | 76 | 64.43 | 10.00 |
| STDD | 1,668 | 830 | 70.05 | 10.00 |
| STE | 801 | 659 | 60.78 | 10.00 |
| STTC | 1,158 | 526 | 68.02 | 10.00 |
| STTU | 176 | 134 | 62.05 | 10.00 |
| TWC | 7,043 | 3,903 | 66.48 | 10.00 |
| TWO | 2,877 | 1,505 | 68.00 | 10.00 |
| UW | 136 | 57 | 73.19 | 10.00 |
| VEB | 56 | 41 | 71.16 | 10.00 |
| VFW | 116 | 77 | 70.80 | 10.00 |
| VPB | 294 | 171 | 70.74 | 10.00 |
| VPE | 12 | 6 | 48.83 | 10.00 |
| WPW | 72 | 44 | 43.06 | 10.00 |
| SB | 16,559 | 10,474 | 58.17 | 10.00 |
| SR | 8,125 | 3,609 | 52.29 | 10.00 |
| AFIB | 1,780 | 1,041 | 73.24 | 10.00 |
| ST | 7,255 | 3,750 | 50.90 | 10.00 |
| AF | 8,060 | 4,756 | 72.53 | 10.00 |
| SA | 2,550 | 1,456 | 37.79 | 10.00 |
| SVT | 724 | 346 | 55.74 | 10.00 |
| AT | 297 | 163 | 69.44 | 10.00 |
| AVRT | 26 | 9 | 62.73 | 10.00 |

2) CPSC 2018 [16]: This multi-label dataset was derived from the China Physiological Signal Challenge 2018: Automatic identification of the rhythm/morphology abnormalities in 12-lead ECGs, which contains 6,877 12-lead ECG records from 11 hospitals for training and testing. The ECG records are sampled at 500 Hz, and the signal length of the data is from 6 to 60 seconds. The labels of these records include one normal type and

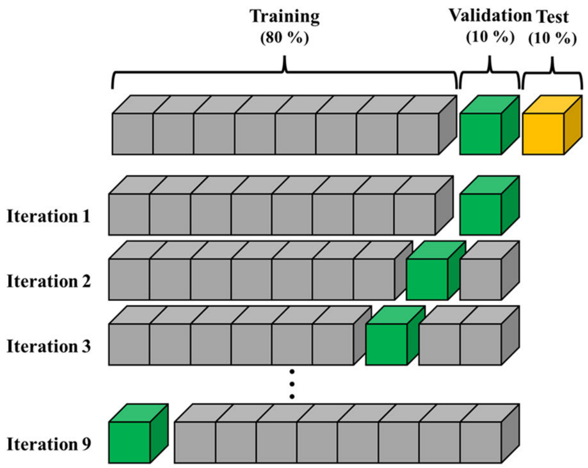


**FIGURE 6.** Our 12-lead ECG data division and the 9-fold cross-validation method.

eight abnormal types, which are detailed as sinus normal rhythm (SNR), atrial fibrillation (AF), first-degree atrioventricular block (1AVB), left bundle branch block (LBBB), right bundle branch block (RBBB), premature atrial contraction (PAC), premature ventricular contraction (PVC), ST-segment depression (STD) and ST-segment elevated (STE). As the CNN requires inputs to be the same length, the data longer than 10 seconds were cropped, and those smaller than 10 seconds were padded with zeros.

### B. IMPLEMENTATION DETAILS

1) k-fold cross-validation: For the proposed network training, evaluation, and testing, we applied a 9-fold cross-validation approach. First, the dataset was randomly divided into ten folds. Secondly, we utilized eight out of the ten folds for training and one-fold out of the ten folds for validation in each iteration. Finally, the remaining fold is used for testing, and the average performance of the proposed classification network is produced. Fig. 6 shows our 12-lead ECG data division and the 9-fold cross-validation method.
2) Training details: The proposed network is implemented on the Intel(R) Xeon(R) Gold 6138 processor, AMD Ryzen Threadripper 3960X 24-Core processor, NVIDIA RTX 3090 GPU, Python 3.7.11, and Pytorch framework version 1.12.0+cu1 02. We conducted 200 repeated training sessions on the 45,152 12-lead ECG data. The fixed learning rate was set to 0.0001, and we used the Adam optimizer [36]. The batch size = 64, and nine iterations were run for each epoch since we adopted the 9-fold cross-validation method. Due to the multi-label classes in the dataset, we use the binary cross entropy (BCE) with logits loss (BCEWithLogitsLoss) function, which combines the sigmoid layer and the BCE loss to achieve numerical stability.

### C. EVALUATION CRITERIA

This paper adopts the average precision, recall, F1 score, area under the receiver operating characteristic (AUROC) curve, and accuracy score for classification performance. The details are as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \tag{10}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

True positive ($TP$) is the number of true positive samples correctly predicted as positive. In other words, it indicates the cases where the model correctly classifies true positives. True negative ($TN$) represents the number of true negative samples correctly predicted as negative. This shows the cases where the model correctly classifies true negatives. False positive ($FP$) is false positive, the number of true negative samples incorrectly predicted as positive. This indicates the cases where the model wrongly classifies false positives. False negative ($FN$) represents the number of true positive samples incorrectly predicted as negative. This shows the cases where the model wrongly classifies false negatives. To better evaluate the multi-label classification performance, the average of five metrics among classes was calculated to give a final evaluation. Among these metrics, the F1 score mainly assesses the recognition effect, the most critical evaluation metric in cardiac arrhythmia classification.

### D. IMPLEMENTATION RESULTS USING A LARGE-SCALE 12-LEAD ECG DATABASE FOR ARRHYTHMIA STUDY

To validate the performance of our proposed network, we compared it with recently developed CNN-based cardiac arrhythmia classification networks. Table 3 compares average precision, recall, average F1 score, average AUROC, and average accuracy between six reference models and our proposed network for arrhythmia classification. These evaluations were conducted using a large-scale 12-lead ECG database for the arrhythmia study dataset [18]. Considering the F1 score of each CNN-based cardiac arrhythmia classification network, the proposed network shows the highest performance. Specifically, SENet-34 has an F1 score of 0.385, and ResNet-34 has an F1 score of 0.261. Compared to SENet-34 and ResNet-34, the proposed classification network achieved an F1 score of 0.028, higher than SENet-34 and 0.125 higher than ResNet-34. Moreover, the proposed classification network exhibits higher F1 scores of 0.07, 0.166, 0.152, and 0.098 compared to other CNN-based networks [19], [20], [21], and [23], respectively.

We compared AUROC and accuracy as well as F1 scores. Table 3 shows that the proposed network exhibits the highest

**TABLE 3.** Classification performance results on a large-scale 12-lead ECG database for arrhythmia study.

| Average Score | Precision | Recall | F1 Score | AUROC | Accuracy |
|---|---|---|---|---|---|
| Our work | **0.394** | **0.533** | **0.413** | **0.962** | **0.956** |
| SENet-34 [30] | 0.364 | 0.498 | 0.385 | 0.959 | 0.955 |
| ResNet-34 [32] | 0.234 | 0.435 | 0.261 | 0.875 | 0.857 |
| [19] | 0.292 | 0.452 | 0.315 | 0.928 | 0.910 |
| [20] | 0.392 | 0.529 | 0.406 | 0.959 | 0.934 |
| [21] | 0.226 | 0.485 | 0.247 | 0.888 | 0.806 |
| [23] | 0.272 | 0.444 | 0.288 | 0.884 | 0.882 |

**TABLE 4.** Classification performance results on CPSC 2018 dataset.

| Average Score | Precision | Recall | F1 Score | AUROC | Accuracy |
|---|---|---|---|---|---|
| Our work | 0.793 | **0.776** | **0.775** | 0.951 | **0.957** |
| SENet-34 [30] | 0.744 | 0.710 | 0.717 | 0.944 | 0.946 |
| ResNet-34 [32] | 0.630 | 0.546 | 0.577 | 0.883 | 0.922 |
| [19] | 0.709 | 0.735 | 0.716 | 0.943 | 0.940 |
| [20] | **0.813** | 0.729 | 0.763 | **0.959** | 0.956 |
| [21] | 0.605 | 0.643 | 0.605 | 0.895 | 0.903 |
| [23] | 0.662 | 0.694 | 0.663 | 0.915 | 0.928 |

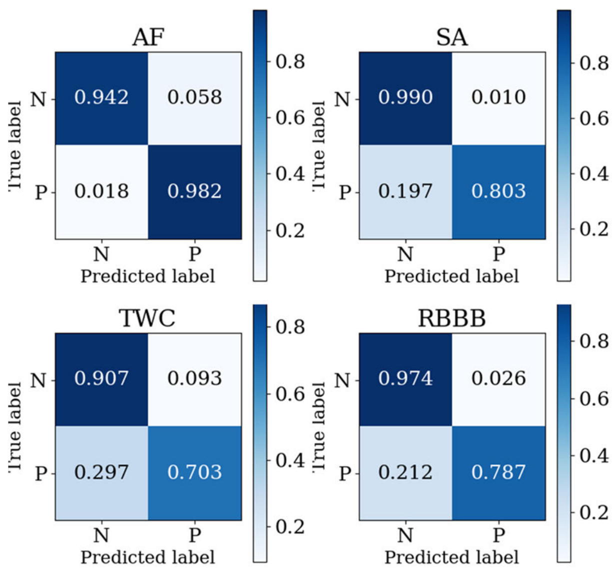


**FIGURE 7.** Confusion matrix for AF, SA, TWC, and RBBB.

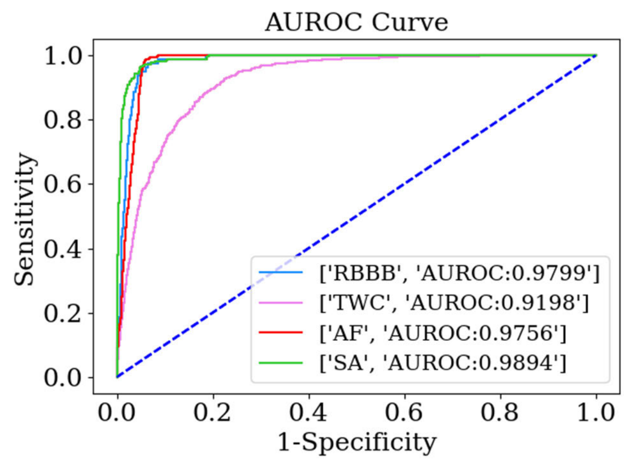


**FIGURE 8.** AUROC curve for AF, SA, TWC, and RBBB.

AUROC and accuracy. Specifically, comparing the AUROCs of SENet-34 and ResNet-34 improved by 0.003 and 0.087, respectively. When compared with the other four cardiac arrhythmia classification networks [19], [20], [21], and [23], it can be seen that the AUROC is improved by 0.003, 0.074, 0.070, and 0.034, respectively. In addition, improvements of 0.001, 0.099, 0.022, 0.150, 0.074, and 0.046 were observed when comparing the six different classification networks in accuracy, respectively.

In summary, the proposed classification network performs well in all average evaluation metrics (precision, recall, F1 score, AUROC, and accuracy). Table 3 shows the average of each evaluation metric. Furthermore, the F1 score results for each arrhythmia class using a large-scale 12-lead ECG database for arrhythmia study in the proposed network and six other 12-lead ECG classification networks are summarized in Table 5. In Table 5, 0.000 means that the network failed to perform a single classification. Additionally, we present the confusion matrix and AUROC curve for atrial flutter (AF), sinus irregularity (SA), T wave change (TWC), and RBBB in Fig. 7 and 8. Confusion matrix and AUROC curve are used to verify that an implemented network. In addition, a large AUROC curve area means that the network performs well. Specifically, our proposed network shows superior performance for AF, SA, TWC, and RBBB, as shown in Fig. 7 and 8.

**TABLE 5. F1 score results in each arrhythmia class using a large-scale 12-lead ECG database for arrhythmia study.**

| Class | F1 Score | | | | | | |
|---|---|---|---|---|---|---|---|
| | Our work | SENet-34 [30] | ResNet-34 [32] | [19] | [20] | [21] | [23] |
| 1AVB | 0.658 | **0.682** | 0.518 | 0.634 | 0.628 | 0.322 | 0.629 |
| 2AVB | **0.286** | 0.000 | 0.000 | 0.100 | 0.000 | 0.027 | 0.000 |
| 2AVB1 | 0.000 | 0.000 | **0.002** | **0.002** | 0.000 | **0.002** | **0.002** |
| 3AVB | 0.364 | **0.429** | 0.000 | 0.381 | 0.364 | 0.214 | 0.000 |
| ALS | 0.542 | 0.619 | 0.532 | 0.531 | **0.627** | 0.477 | 0.571 |
| APB | 0.757 | 0.589 | 0.125 | 0.562 | **0.767** | 0.110 | 0.169 |
| AQW | 0.487 | **0.517** | 0.343 | 0.383 | 0.440 | 0.368 | 0.409 |
| ARS | 0.442 | 0.510 | 0.407 | 0.438 | **0.527** | 0.462 | 0.460 |
| AVB | **0.189** | 0.168 | 0.043 | 0.148 | 0.115 | 0.120 | 0.071 |
| CCR | 0.118 | 0.059 | 0.034 | 0.000 | 0.102 | **0.154** | 0.036 |
| CR | 0.233 | 0.148 | 0.003 | 0.073 | **0.353** | 0.003 | 0.003 |
| ERV | **0.409** | 0.394 | 0.253 | 0.322 | 0.378 | 0.119 | 0.295 |
| IVB | 0.533 | 0.446 | 0.108 | 0.157 | **0.534** | 0.160 | 0.120 |
| JEB | 0.235 | 0.000 | 0.000 | 0.100 | **0.267** | 0.071 | 0.075 |
| LFBBB | 0.293 | 0.295 | 0.220 | 0.286 | **0.316** | 0.286 | 0.160 |
| LVH | 0.541 | 0.571 | 0.467 | 0.396 | 0.576 | **0.610** | 0.405 |
| LVQRSAL | 0.481 | **0.542** | 0.489 | 0.426 | 0.510 | 0.216 | 0.401 |
| MISW | **0.308** | 0.235 | 0.125 | 0.000 | 0.143 | 0.000 | 0.069 |
| PRIE | **0.056** | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 |
| PWC | 0.191 | 0.152 | **0.214** | 0.111 | 0.211 | 0.005 | 0.000 |
| QTIE | 0.263 | 0.244 | 0.111 | 0.071 | **0.298** | 0.156 | 0.165 |
| RAH | 0.125 | 0.056 | 0.001 | 0.250 | **0.333** | 0.001 | 0.001 |
| RBBB | **0.487** | 0.453 | 0.470 | 0.429 | 0.458 | 0.424 | 0.361 |
| RVH | 0.364 | 0.342 | 0.296 | 0.000 | 0.400 | 0.353 | **0.424** |
| STDD | 0.468 | **0.487** | 0.403 | 0.433 | 0.466 | 0.437 | 0.395 |
| STE | 0.292 | **0.350** | 0.277 | 0.260 | 0.302 | 0.234 | 0.271 |
| STTC | 0.215 | **0.248** | 0.187 | 0.214 | 0.204 | 0.224 | 0.200 |
| STTU | **0.195** | 0.124 | 0.103 | 0.167 | 0.191 | 0.108 | 0.125 |
| TWC | **0.640** | 0.633 | 0.628 | 0.625 | 0.621 | 0.570 | 0.587 |
| TWO | 0.547 | 0.553 | 0.480 | 0.523 | **0.556** | 0.461 | 0.483 |
| UW | 0.231 | 0.000 | 0.000 | 0.091 | **0.233** | 0.017 | 0.053 |
| VEB | **0.364** | 0.308 | 0.000 | 0.138 | 0.250 | 0.056 | 0.101 |
| VFW | 0.067 | **0.313** | 0.000 | 0.034 | 0.194 | 0.040 | 0.057 |
| VPB | 0.328 | **0.342** | 0.000 | 0.029 | 0.319 | 0.090 | 0.158 |
| VPE | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| WPW | 0.533 | 0.500 | 0.000 | 0.353 | 0.429 | 0.333 | **0.556** |
| SB | 0.985 | 0.975 | 0.960 | 0.984 | **0.991** | 0.916 | 0.968 |
| SR | 0.928 | 0.906 | 0.821 | 0.910 | **0.938** | 0.528 | 0.867 |
| AFIB | **0.336** | 0.323 | 0.293 | 0.319 | 0.336 | 0.302 | 0.314 |
| ST | 0.961 | 0.944 | 0.898 | 0.952 | **0.962** | 0.763 | 0.933 |
| AF | **0.877** | 0.858 | 0.819 | 0.858 | 0.864 | 0.609 | 0.838 |
| SA | **0.814** | 0.708 | 0.373 | 0.640 | 0.808 | 0.212 | 0.445 |
| SVT | 0.803 | 0.766 | 0.688 | 0.818 | **0.850** | 0.543 | 0.703 |
| AT | 0.415 | **0.556** | 0.037 | 0.043 | 0.400 | 0.000 | 0.097 |
| AVRT | **0.222** | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 |

## E. IMPLEMENTATION RESULTS USING CPSC 2018 DATASET

To verify the performance of the proposed cardiac arrhythmia classification network not only on a large-scale 12-lead ECG database for arrhythmia study but also on other datasets, we conducted additional experiments using the CPSC 2018 dataset [16]. Table 4 compares the average precision, average recall, average F1 score, average AUROC, and average accuracy of the proposed network and the six reference models using CPSC 2018. Contrary to the experimental results in a large-scale 12-lead ECG database for arrhythmia study, the proposed network did not perform well in all evaluation metrics when tested on the CPSC 2018 dataset. However, the proposed classification network outperforms other CNN-based classification networks because it performs best in the most important evaluation metric, the F1 score. As a result, the proposed network shows superior performance in terms of precision compared to SENet-34, ResNet-34, [19], [21], and [23]. However, the precision lags slightly [20] by 0.020.

Nevertheless, the proposed network outperforms [20] in the recall by 0.047, resulting in a noticeable improvement in the F1 score by 0.012. Meanwhile, the proposed network outperforms the other six classification networks regarding recall, F1 score, and accuracy. However, compared to [20], performance is weak regarding precision and AUROC. In summary, the proposed network exhibits lower average precision and average AUROC compared to [20]. Still, it ensures classification performance due to its strong performance in the most important performance metric, the F1 score. The F1 score results for each arrhythmia class using the CPSC 2018 dataset in the proposed network and six other 12-lead ECG classification networks are summarized in Table 6. Also, we present the confusion matrix and AUROC curve for atrial fibrillation (AF), LBBB, RBBB, and PAC in Fig. 9 and 10. As shown in Fig. 9 and 10, our proposed classification network performs well for AF, LBBB, RBBB, and PAC.

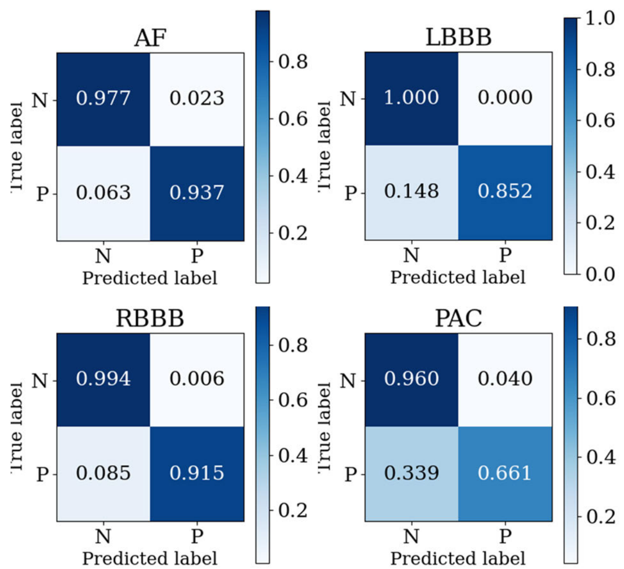


**FIGURE 9. Confusion matrix for AF, LBBB, RBBB, and PAC.**

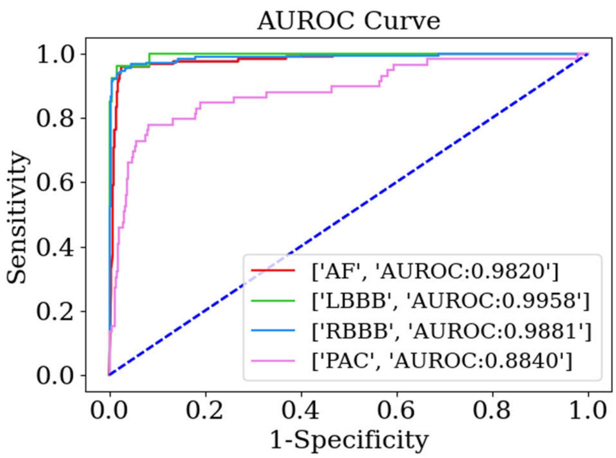


**FIGURE 10.** Confusion matrix for AF, LBBB, RBBB, and PAC.

**TABLE 6.** F1 score results in each arrhythmia class using CPSC 2018.

| Class | F1 Score | | | | | | |
|---|---|---|---|---|---|---|---|
| | Our work | SENet-34 [30] | ResNet-34 [32] | [19] | [20] | [21] | [23] |
| SNR | **0.757** | 0.652 | 0.503 | 0.697 | 0.758 | 0.553 | 0.638 |
| AF | **0.919** | 0.895 | 0.800 | 0.893 | 0.909 | 0.826 | 0.881 |
| 1AVB | 0.901 | 0.859 | 0.588 | 0.842 | **0.915** | 0.480 | 0.836 |
| LBBB | **0.920** | 0.875 | 0.851 | 0.833 | 0.857 | 0.857 | 0.857 |
| RBBB | **0.948** | 0.912 | 0.874 | 0.879 | 0.920 | 0.890 | 0.903 |
| PAC | **0.634** | 0.358 | 0.161 | 0.448 | 0.544 | 0.295 | 0.303 |
| PVC | 0.576 | **0.647** | 0.303 | 0.534 | 0.617 | 0.410 | 0.409 |
| STD | 0.763 | 0.733 | 0.678 | 0.772 | **0.778** | 0.612 | 0.667 |
| STE | 0.553 | 0.519 | 0.432 | 0.542 | **0.571** | 0.526 | 0.473 |

## V. DISCUSSION

The paradigm shift toward training deep learning networks has significantly impacted the size of datasets used to train models. On the other hand, the most convincing papers using deep learning or mixed approaches have constructed large datasets, ranging from 3,000 to 100,000 patients, for training their networks [15], [19], [22], [45], and [46]. Although the datasets used in their research was large, there were still limitations in the types of arrhythmias collected.

In our study, we employed a large dataset [18] containing 51 arrhythmia classes and Jiewei Lai et al. [47] used a large-scale dataset to classify 60 cardiac arrhythmia classes. However, there were still insufficient data samples for some classes, such as ventricular pre-excitation (VPE), second-degree atrioventricular block: type one (2AVB1), ventricular fusion wave (VFW), counterclockwise rotation (CCR), etc. As a result, our proposed network showed limitations in prediction performance in some classes. To address this issue, future studies should focus on acquiring a variety of arrhythmias and a larger number of ECG data samples. This approach is essential to improve classification performance further. In particular, we believe future arrhythmia classification studies will yield more meaningful and clinically valuable results if they collaborate with cardiologists.

Unlike previous studies, the proposed network integrates both the residual structure and channel attention mechanism. As a result, we were able to achieve significant performance improvements. We believe that this will be a great motivation for future research.

## VI. CONCLUSION

In this paper, we conduct the research based solely on ECG data collected to interpret cardiac rhythm disorder [16], [18]. We propose an automated multi-label cardiac arrhythmia classification network based on CNN, which detects and classifies 45 cardiac arrhythmia classes using 12-lead ECG data. Specifically, we developed short residual and global channel attention blocks during training to focus on the main characteristics of each arrhythmia class from the original 12-lead ECG data. The proposed network showed a precision of 0.394, recall of 0.533, f1 score of 0.413, AUROC of 0.962, and accuracy of 0.956 on a large-scale 12-lead ECG database for the arrhythmia study dataset [18]. Moreover, additional experiments conducted using the CPSC 2018 dataset [16] showed that the proposed network exhibited a precision of 0.793, recall of 0.776, f1 score of 0.775, AUROC of 0.951, and accuracy of 0.957. Compared with the existing CNN-based arrhythmia classification networks, our proposed network shows outstanding performance for cardiac arrhythmia classification on two public datasets. The experimental results convince the effectiveness of the proposed method.

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**HO KEUN KIM** (Graduate Student Member, IEEE) received the B.S. degree in electrical and electronics engineering from Ajou University, Suwon, South Korea, in 2016, where he is currently pursuing the combined M.S. and Ph.D. degree in electrical and electronic engineering. From 2019 to 2022, he was with the Research and Development Center, Danam Systems Corporation, Anyang, South Korea, as a Senior Research Engineer. His current research interests include deep learning, telemetry systems, digital signal processing, cryptography, and digital logic design on ASIC and FPGA.

**MYUNG HOON SUNWOO** (Life Fellow, IEEE) received the B.S. degree from Sogang University, in 1980, the M.S. degree in electrical engineering from Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 1982, and the Ph.D. degree in electrical and computer engineering from The University of Texas at Austin, Austin, TX, USA, in 1990. He was with ETRI, Daejeon, from 1982 to 1985, and Digital Signal Processor Operations, Motorola, from 1990 to 1992. Since 1992, he has been with the Department of Electrical and Computer Engineering, Ajou University, Suwon, South Korea, where he is currently a Professor. He is also the Director of the Medical Image-Based Intelligent Diagnostic Solutions (MIIDS) Research Center. He has authored numerous papers, held more than 120 patents, and won more than 60 awards. His research interests include artificial intelligence circuits and systems, low-power algorithms and architectures, medical imaging diagnosis, and deep-learning-based channel coding. He has been a Distinguished Lecturer at the IEEE Circuits and Systems Society (CASS), from 2009 to 2010. He has served on the CASS Board of Directors (BoG), from 2011 to 2016, and the IEEE CASS VP of Conferences, from 2018 to 2021. As the IEEE CASS VP of Conferences, he founded the IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS), in 2019. He is the IEEE CASS President. He served as the General Chair for the International Symposium on Circuits and Systems (ISCAS), Seoul, South Korea, in 2012, and the General Co-Chair of ISCAS 2021, Daegu, South Korea. He was an Associate Editor of IEEE TRANSACTIONS ON VERY LARGE SCALE INTEGRATION (VLSI) SYSTEMS, from 2002 to 2003, and a Co-Editor of several books, including *Selected Topics in Biomedical Circuits and Systems* (River Publishers Series in Circuits and Systems, 2021).