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SELF-ORGANIZED OPERATIONAL NEURAL NETWORKS FOR THE DETECTION OF ATRIAL FIBRILLATION

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Abstract

Atrial fibrillation is a common cardiac arrhythmia, and its incidence increases with age. Currently, numerous deep learning methods have been proposed for AF detection. However, these methods either have complex structures or poor robustness. Given the evidence from recent studies, it is not surprising to observe the limitations in the learning performance of these approaches. This can be attributed to their strictly homogenous conguration, which solely relies on the linear neuron model. The limitations mentioned above have been addressed by operational neural networks (ONNs). These networks employ a heterogeneous network configuration, incorporating neurons equipped with diverse nonlinear operators. Therefore, in this study, to enhance the detection performance while maintaining computational efficiency, a novel model named multi-scale Self-ONNs (MSSelf-ONNs) was proposed to identify AF. The proposed model possesses a significant advantage and superiority over conventional ONNs due to their self-organization capability. Unlike conventional ONNs, MSSelf -ONNs eliminate the need for prior operator search within the operator set library to find the optimal set of operators. This unique characteristic sets MSSelf -ONNs apart and enhances their overall performance. To validate and evaluate the system, we have implemented the experiments on the well-known MIT-BIH atrial fibrillation database. The proposed model yields total accuracies and kappa coefficients of 98% and 0.95, respectively. The experiment results demonstrate that the proposed model outperform the state-of-the-art deep CNN in terms of both performance and computational complexity.

Keywords: convolutional neural network, operational Neural Networks, atrial fibrillation detection, ECG classification.

1 Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia and is associated with high mortality and morbidity rates in many cardiovascular diseases [1]. Currently, the global prevalence of AF is 1%-2% of the total population, and it is expected to triple by the year 2050 [2]. Research indicates that AF increases the risk of stroke by five times compared to the general population, and the mortality rate of ischemic stroke associated with atrial fibrillation is nearly twice as high as that of non-atrial fibrillation cases [3]. It is a cardiovascular disease that requires urgent medical attention [4]. In the early stages, atrial fibrillation often manifests as paroxysmal and asymptomatic. If left untreated, it may progress to persistent or even permanent atrial fibrillation, making rhythm restoration more challenging [5-6]. Therefore, accurate diagnosis of AF is crucial in preventing its further progression to other heart diseases and stroke complications.

Common methods for detecting atrial fibrillation include pulse palpation, photoplethysmography, oscillographic blood pressure, and electrocardiogram (ECG) diagnosis [7]. Among them, ECG diagnosis is the gold standard for clinical testing of atrial fibrillation [7]. The characteristics of the ECG during the occurrence of atrial fibrillation include the absence of P-waves, highly irregular variations in R-R intervals, and the presence of undulating atrial activity [8]. Conventional ECG monitoring requires patients to be in a fixed medical setting and lie down for a limited period of time. Within this limited time, only a small amount of information about the heart's condition can be obtained. However, paroxysmal and intermittent atrial fibrillation episodes are often short, typically lasting only a few seconds [9]. Conventional ECG monitoring is challenging to capture these brief episodes of the disease. To address this, 24-hour ambulatory ECG monitoring devices and wearable monitoring devices are used to record longer periods of cardiac activity, enabling the detection of occasional or paroxysmal abnormal cardiac activity [10]. However, ECG signals are susceptible to external noise interference, such as power line interference, electrode contact noise, and motion artifacts, resulting in ECG morphological changes [11]. Even for an experienced clinical physician, it is time-consuming and laborious to observe various abnormal cardiac rhythm changes from long-term ECG recordings. There is also a risk of missed diagnoses. Therefore, many researchers have proposed automatic detection algorithms for atrial fibrillation to improve the diagnostic efficiency of doctors [12-13].

In general, the AF detection methods can be categorically grouped into two groups: manual feature extraction methods and automatic feature learning methods. The RR interval (RRI) features and atrial activity (AA) features are mainly used for the first method. Rahul et at. [14] utilize the RR interval approach revealed the presence of three distinct types of arrhythmia, including atrial rhythm. Based on the RR interval, Chen et al. [15] combined ten signal features together to diagnose heart disorders. Hirsch et al. [16] proposed a hybrid approach utilizes features related to both the RRI and AA. They obtained state-of-the-art classification performance. Millán et al. [17] applied empirical mode decomposition to analyze the denoised ECG signal and transformed the processed signal into its corresponding mode function to extract the P wave features for the purpose of atrial fibrillation detection. In the study presented in [18], a method was introduced that utilizes the mean instantaneous frequency of the ST intervals to provide a quantitative assessment of the risk of sudden cardiac deaths. Udawat et al. [19] proposed a new approach for automated AF detection by using a set of time-domain, frequency-domain and nonlinear features from the RR intervals. Grégoire et al. [20] initially employed wavelet transform to process the ECG signals, and subsequently selected 44 ECG features for the detection of AF. Although these studies have achieved good classification performance, they necessitate domain expertise and typically perform effectively on ECG data that is free from noise or artifacts.

In contrast to conventional methods mentioned above, deep learning approaches have the advantage of automatically extracting deep features, thereby enhancing accuracy without heavy reliance on expert knowledge. As a result, researchers have made significant efforts to utilize deep learning methods for atrial fibrillation (AF) detection, leading to state-of-the-art results [21]. Petmezas et al. [22] developed a hybrid CNN-LSTM network to enhance the classification of AF in imbalanced ECG datasets. Their approach achieved a sensitivity of 97.87% and specificity of 99.29%, demonstrating its effectiveness in accurately identifying AF cases.Tran et al. [23] proposed a novel model, MultiFusionNet, where two sub-networks are combined within single network architecture. This unique design has shown promising performance, even when trained with a limited dataset. Shi et al. [24] introduced a loop-locked framework for the identification of atrial fibrillation (AF), utilizing transfer learning and active learning. Jin et al. [25] introduced a novel approach called Domain Adaptive Residual Network to detect atrial fibrillation (AF) in unlabeled datasets by leveraging the detection knowledge obtained from labeled datasets. A novel AF detection model has been proposed in reference [26], incorporating a conglomerate parallel structure of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) framework. This architecture aims to enhance feature comprehension and classification capabilities for improved AF detection. Gündüz et al. [27] used bidirectional long short-term memory (BiLSTM) network for AF classification based on spectral features and P waves. BiLSTM networks, which can capture time-sensitive features of ECG, have demonstrated superior performance compared to cascades of CNN and long short-term memory (LSTM) networks. Rahul et al. [28] proposed a BiLSTM network that detects AF by using one-dimensional electrocardiogram signals and their time-frequency representations as inputs. Ding et al. [29] developed a log-spectral matching GAN model for AF detection, which serves as a data augmentation method to address class imbalance.

Although these methods mentioned have shown impressive classification performance, they rely on deep CNNs with complex architectures. Additionally, these approaches demand a substantial amount of labeled ECG data for training. Furthermore, their implementation is hindered by the necessity for specialized parallelized hardware, making them unsuitable for direct deployment on low-power or mobile devices [30].

Based on recent research findings, [31-34], CNNs and their predecessors, Multi-Layer Perceptrons (MLPs), share a common reliance on the ancient linear neuron model. As a result, they excel in effectively learning problems that can be linearly separated. This means that when the data can be easily divided into distinct classes by a straight line or plane, CNNs and MLPs perform admirably. However, these models may encounter significant difficulties or even experience complete failure when confronted with problem domains that exhibit high levels of nonlinearity and complexity. In such scenarios, where the solution space is intricate and nonlinear, the linear neuron model proves insufficient for capturing the underlying patterns and relationships, leading to compromised performance or outright failure of these models. To overcome the aforementioned limitations, a recent development in neural network models called Operational Neural Networks (ONNs) [35] has been proposed. Unlike traditional CNNs and MLPs, ONNs are designed as heterogeneous network models that incorporate various types of nonlinear neurons. This diversification of neuron types allows ONNs to capture and model complex nonlinear relationships within the data more effectively [36]. The incorporation of distinct nonlinear neurons in ONNs offers a promising approach to address the challenges posed by highly nonlinear and complex problem domains [36]. However, ONNs, too, have a variety of limits and downsides as a result of such fixed and static architecture [37]. Firstly, the availability of operators is constrained to those present in the operator set library. If the required operator set for a specific learning problem is not included in the library, achieving the desired learning performance becomes unattainable [37]. Secondly, in order to simplify the search space, a reduced number of operator sets can be allocated to all neurons within each hidden layer, resulting in a limited level of heterogeneity [38]. This compromises the network's ability to explore diverse computati onal capabilities. Lastly, the process of searching for the optimal operator sets for each layer is an ongoing necessity, particularly for deeper networks [38]. This search can be laborious and time-consuming, further adding to the challenges associated with ONNs.

In order to address the challenges mentioned above, Kiranyaz et al. [37] introduced self-organized operational neural networks (Self-ONNs) with generative neurons. The key innovation in Self-ONNs is the incorporation of generative neuron models, enabling the networks to self-organize during the back-propagation (BP) training process. This self-organization is achieved by iteratively generating nodal operators that aim to maximize the learning performance [37]. By leveraging the generative neuron model, Self-ONNs gain the ability to create various non-linear nodal operators, which significantly enhances their operational diversity and flexibility. Self-ONNs represent an advanced extension of conventional CNNs [39]. While CNNs rely on a homogenous network structure with linear neuron models, Self-ONNs introduce a heterogeneous network architecture featuring a "self-generating" non-linear neuron model known as generative neurons. This fundamental difference allows Self-ONNs to exhibit superior diversity and achieve enhanced learning performance [39].

In this study, a novel model called Multi-Scale Self-ONNs (MSSelf-ONNs) is proposed, which utilizes multi-scale kernel to extract different scale features. This will leads to more accurate classification. To accomplish a multi-scale feature representation, incepting model is integrated into the Self-ONNs. The rest of the paper is structured as follows: Section 2 provides an overview of the ECG datasets utilized in the study. Section 3 presents the proposed approach in detail. The performance of the proposed model is evaluated in Section 4 by utilizing standard performance metrics. The obtained results are then compared with those achieved by recent state-of-the-art approaches. Lastly, Section 5 concludes the paper by summarizing the findings and implications of the study. It also provides suggestions for potential areas of future research.

2 Materials

2.1 Dataset

To validate the feature categorization performed by the proposed model, this study utilizes the ECG signals from the MIT-BIH AF database which can be download from https://physionet.org/content/afdb/1.0.0/. The database consists of signals from various cardiac rhythms, including Atrial Fibrillation (AF), Normal-Atrial Fibrillation (N-AF), and Normal Sinus Rhythm (NSR). These datasets are employed to evaluate and validate the effectiveness of the proposed model in accurately categorizing the features. The database contains 25 long-term recordings of ECG signals obtained from patients. Specifically, it consists of 23 records, each from a different patient. These recordings are unique and have a duration of 10 hours. The ECG signals were sampled at a rate of 250 Hz, meaning that 250 data points were collected per second. The signal span, which represents the range of voltage values, was +/- 10 mV. The recordings were digitized with a resolution of 12 bits, allowing for precise measurement and representation of the signal. Based on the information provided in Res. [25], the recordings labeled as "00735" and "03665" are unavailable. Additionally, the recordings labeled as "04936" and "05091" contain incorrect reference annotations. As a result, these four recordings are excluded from the dataset used in this study. The remaining 21 recordings are used to build the dataset for this research. Table 1 displays the rhythm annotation files created by expert cardiologists. They categorized ECG rhythms into four types: normal (N), atrial fibrillation (AFIB), atrial flutter (AFL), and AV junctional rhythm (J). Each rhythm was marked and documented separately by the cardiologists. In this study, AFL, J, and N are attributed to non-AFIB category. Therefore, samples were assigned a binary classification as "AFIB" or "Not-AFIB".

2.2 Data Preprocessing

The initial stage of data preprocessing typically involves applying a technique to remove noise from the ECG signal. Two primary types of noise can potentially corrupt an ECG signal: high-frequency noise, such as powerline interference and Gaussian white noise, and low-frequency noise, which includes baseline wander noise among other factors [22]. According to Res. [22] a 7-th order Butterworth high-pass filter was utilized with a cutoff frequency of 0.5 Hz. The purpose of this filter was to eliminate baseline wander noise.

Table 1. The category distribution of the MIT-BIH AF dataset

Lable	class	number of beats
0	N	619345
1	AFIB	345241
2	AFL	5241
3	J	182

Based on the characteristic variability of R Peak-to-Peak duration in AFIB, it was hypothesized that including a minimum of 3 beats in each analysis segment would be beneficial [40]. According to Res. [40], the duration of ECG segments used in this study was 6 s. Therefore, a segment contains 1500 samples. Each consecutive segment is non-overlapping. These points are taken as the input of the proposed model.

3 Methodology

3.1 Self-organized Operational Neural Networks

CNN and Multi-Layer Perceptrons (MLPs) both employ a "linear" neuron model. However, CNNs introduce two additional restrictions: kernel-wise limited connections and weight sharing. These restrictions transform the linear weighted sum used in MLPs into the convolution formula utilized in CNNs. Figure 1 (left) provides an illustration of this transformation, showcasing three consecutive convolutional layers without sub-sampling (pooling) layers. On the other hand, operational neural networks draw inspiration from Generalized Operational Perceptrons (GOPs) and expand upon the application of linear convolutions in convolutional neurons through the incorporation of nodal and pool operators. These operators form the operational layers and neurons within ONN. Additionally, ONNs inherit the two fundamental restrictions of weight sharing and limited (kernel-wise) connectivity from conventional CNNs.

In Figure 1 (left), we describe the situation of the k-th neuron in the l-th layer of a convolutional neural network. The output of the k-th CNN neuron can be represented as follows [41]:

$$\mathrm{x}_{\mathrm{k}}^{\mathrm{l}}=\mathrm{b}_{\mathrm{k}}^{\mathrm{l}}+\sum_{\mathrm{i}=0}^{\mathrm{N}_{\mathrm{l}-1}}\mathrm{x}_{\mathrm{ik}}^{\mathrm{l}} \tag{1}$$

where b_k^l is the bias of the k-th CNN neuron, and x_{ik}^l is the result of convolution operation.

$$\mathrm{x}_{\mathrm{ik}}^{\mathrm{l}}=\mathrm{Conv2d}(\mathrm{w}_{\mathrm{ik}},\mathrm{y}_{\mathrm{i}}^{\mathrm{l}-1}) \tag{2}$$

In equation (2), Conv2d represents the 2D convolution operation. By definition, the convolution operation can be written as [41]:

$$x_{ik}^{l}(m,n)=$$

$$\sum_{r=0}^{K-1}\sum_{t=0}^{K-1}w_{ik}^{l}(r,t)y_{i}^{l-1}(m+r,n+t) \tag{3}$$

The operational neuron [35] generalizes the convolution operation in CNN as follows [41]:

$$\tilde{\mathrm{x}}_{\mathrm{ik}}^{\mathrm{l}}(m,n)=$$

$$\mathrm{P}_{\mathrm{k}}^{\mathrm{l}}\left({}_{\mathrm{k}}^{\mathrm{l}}\left(\mathrm{w}_{\mathrm{ik}}^{\mathrm{l}}(\mathrm{r},\mathrm{t}),\mathrm{y}_{\mathrm{i}}^{\mathrm{l}-1}(\mathrm{m}+\mathrm{r},\mathrm{n}+\mathrm{t})\right)\right)_{(\mathrm{r,t})=(0,0)}^{(\mathrm{K}-1,\mathrm{K}-1)} \tag{4}$$

where $\varphi_k^l$and $P_k^l$are named as nodal and pool operators, respectively. In a heterogenous ONN configuration, each neuron is assigned a unique combination of φ and P operators. How to choose the appropriate operators are difficult [35]. According to Res [37], Self-ONNs utilize a composite nodal function that is dynamically generated and adjusted through iterative backpropagation, employing a Taylor series-based function approximation. The Taylor series expansion of an infinitely differentiable function $f(\mathrm{x})$ about a point a =0 is given as:

$$f(x)=\sum_{n=0}^{\infty}\frac{f^{(n)}(0)}{n!}x^{n} \tag{5}$$

The q-th order truncated approximation, also known as the Taylor polynomial, can be represented by a finite summation expressed as follows:

$$f(x)^{(Q)}=\sum_{n=0}^{Q}\frac{f^{(n)}(0)}{n!}x^{n} \tag{6}$$

The aforementioned formulation can effectively approximate any function, denoted as (x), with a high degree of accuracy in the vicinity of 0. If the activation function restricts the input feature maps of the neuron around 0, such as the hyperbolic tangent (tanh) function, the formulation described in equation (2) can be utilized to construct a composite nodal operator. In this composite operator, the power coefficients, represented as $\frac{f^{(n)}(0)}{n!}$, can be learned parameters of the network during the training process. In Res. [42], it was demonstrated that the nodal operator of the k-th generative neuron in the l-th layer can be expressed in the following general form:

$$f_{l}^{k}(Y_{l-1},W_{l}^{k},Q)=\sum_{n=0}^{Q}Y_{l-1}^{q}\otimes W_{l}^{k(q)} \tag{7}$$

where Y_{l-1}^{q} is the corresponding input and W_l^k is the three-dimensional weight matrix and $W_l^{k(q)}$ is the q-

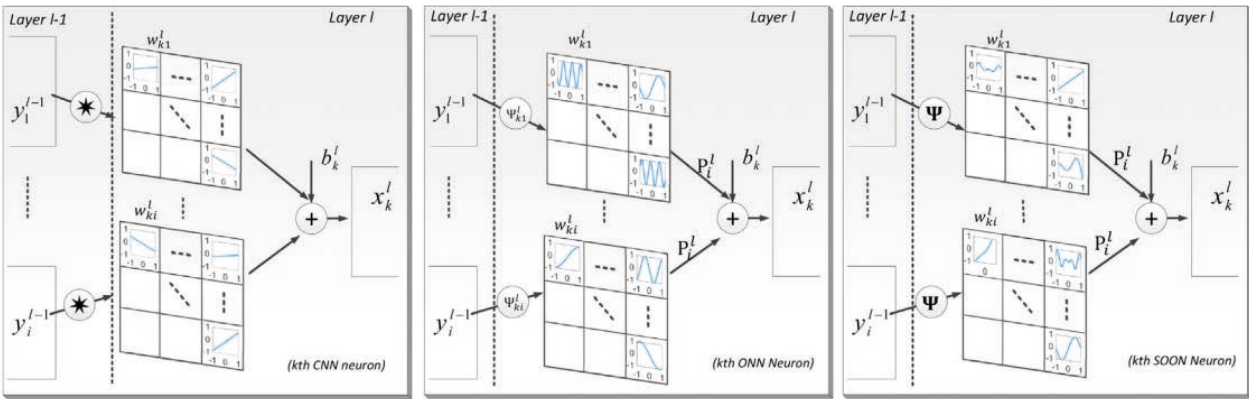

Figure 1. An illustration of the nodal operations in the kernels of the k-th CNN (left), ONN (middle), and Self-ONN (right) neurons at layer l [37].

th slice of W_l^k. For more comprehensive information regarding the theory and formulations of Self-ONNs, please refer to [42]. It provides detailed explanations and insights into the theory and forward propagation of Self-ONN.

3.2 Multi-Scale Self-ONNs

The multi-scale approach allows for the detection of various ECG signal characteristics, such as P waves, QRS complexes, and T waves, at different scales. Different scales may correspond to different physiological phenomena, such as high-frequency components indicating fast-changing electrical activity and low-frequency components representing slower cardiac processes. By considering multiple scales, the classification algorithm can take into account both broad patterns and fine details, leading to improved accuracy and robustness in identifying different types of cardiac conditions, arrhythmias, or abnormalities [43]. The utilization of multi-scale ECG representation is an important factor in enhancing the effectiveness of ECG signal classification algorithms and improving the overall diagnostic capabilities in cardiology. Therefore, a Multi-Scale Self-ONNs model is proposed in this study for the detection of AF. Figure 2 illustrates the overall framework of the automated atrial fibrillation detection. To extract multi-scale features, the kernels of different sizes, such as 3 x 1, 15 x 1, et al., are used. Only three operational layers and three pooling layers are used.

The hyperparameter Q determines the level of approximation in the Taylor series. When Q is equal to 1, Self-ONNs model degenerates into a common convolutional network. When Q takes a larger value, the computational cost of the proposed model will be increased. How to choose a suitable Q value will be presented in the section 4.

4 Experiment

4.1 Evaluation Metrics

To assess the classification performance of the proposed model, all experimental results are measured using specificity, sensitivity, F1 score, total accuracy (TAC), and kappa coefficient (KP) [44-45].

$$\text{TAC} = \frac{TP+TN}{TP+FN+FP+TN}\%$$

$$sensitivity = \frac{TP}{TP+FN}\%$$

$$\text{specificity} = \frac{TN}{TN+FP}\%$$

$$\text{PPV} = \frac{TP}{FP+TP}\%$$

$$\text{NPV} = \frac{TN}{TN+FN}\%$$

The classification performance of the proposed model is comprehensively measured using the F1 score, which is calculated using the formula (2 * recall * precision) / (recall + precision). The true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are denoted by these terms. In this study, a ten-fold cross-validation approach is employed. The experiments were conducted using MATLAB 2019a and Python Google Tensorflow 2.0, running on a machine with 64 GB memory and an NVidia Geforce GTX 3080 GPU.

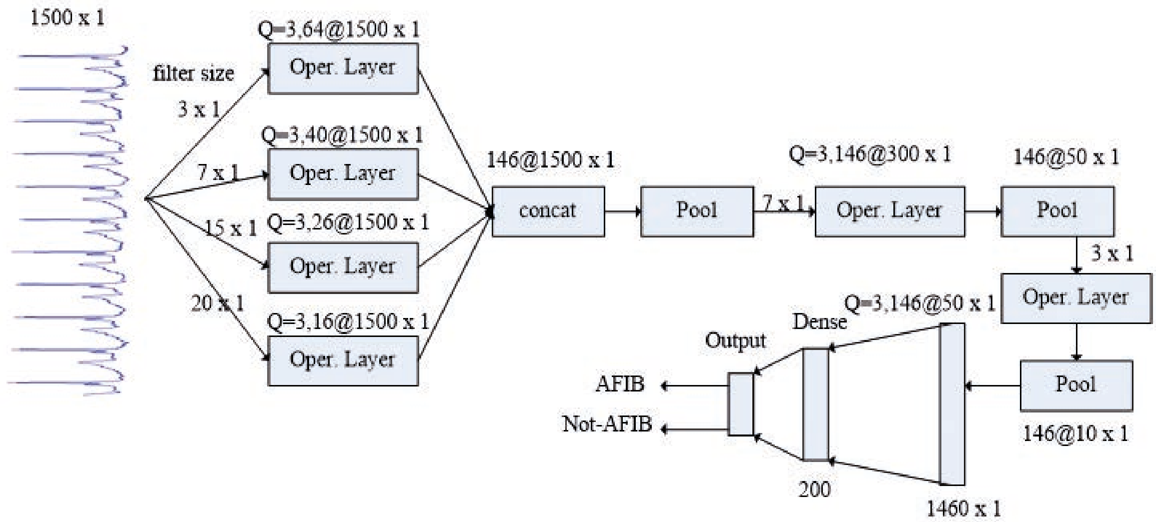

Figure 2. The proposed MSSelf-ONNs framework.

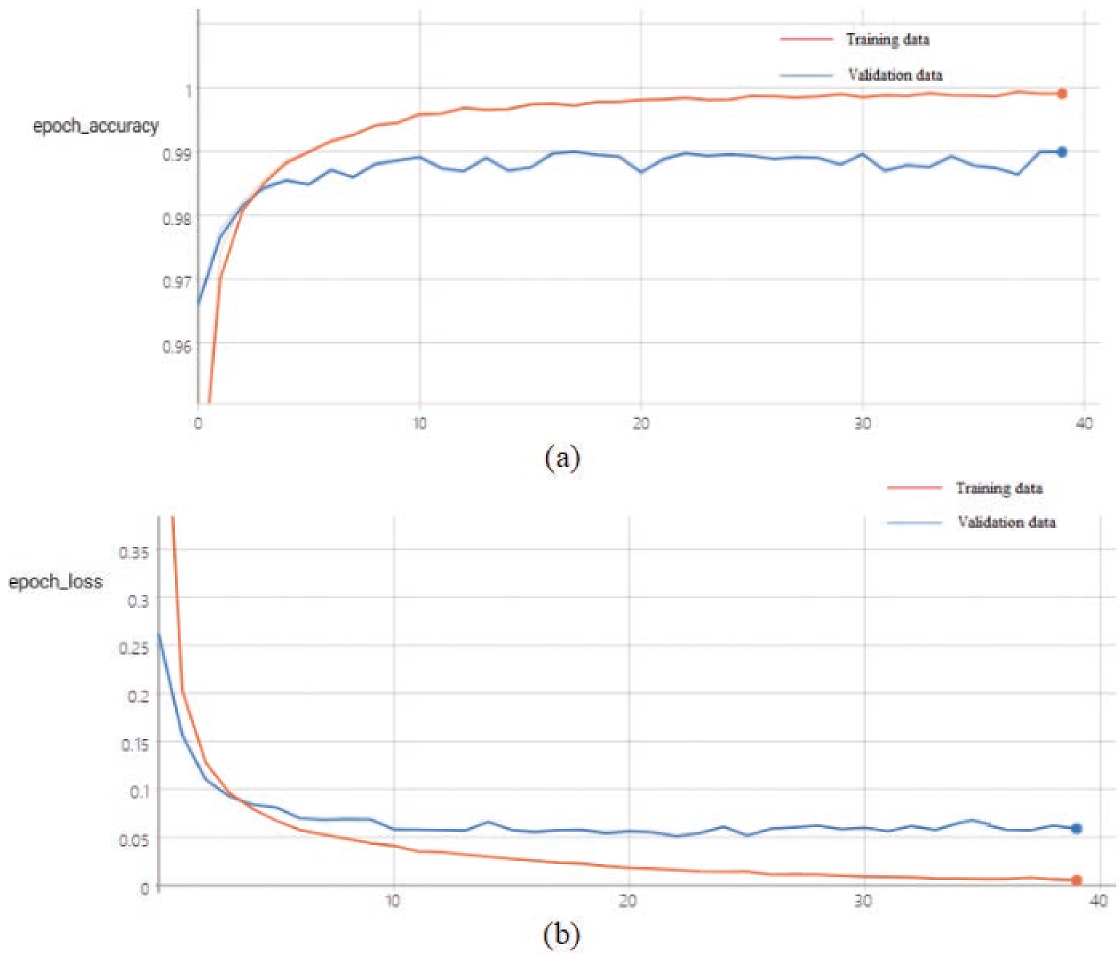

Figure 3. Accuracy and loss of the proposed model for automated AF detection.

4.2 Experimental Setup

The 1D MSSelf-ONNs model, depicted in Figure 2, has been implemented in our study. This model is designed with the primary objective of extracting learned features through three operational layers. These learned features are then combined with two dense layers to analyze and classify the data. The rst operational layer is used to extract multi-scale features, consisting of 64, 40, 26 and 16 neurons respectively, followed by a max-pooling layer of size 5 x 1. The second operation layer is composed of 146 neurons with a filter size of 7 x 1, followed by a max-pooling layer of size 6 x 1. The third operation layer is composed of 146 neurons with a filter size of 3 x 1, followed by a max-pooling layer of size 5 x 1. The nonlinear activation function tanh is used in MSSelf-ONN. The Adam optimizer is employed in this study, with a learning rate (LR) set to 0.001. Additionally, an LR scheduler is implemented, which decreases the LR by a factor of 0.02 every 10 epochs. The Kaiming initializer was utilized to initialize the weights of the model. The model was trained for 40 epochs using a batch size of 64.

4.3 Results

The training and validation accuracies and losses of the proposed MSSelf-ONN model at each epoch were visualized in Figure 3. The validation curve closely resembled the training curve. This alignment between the two curves indicates that the model did not experience overfitting. Figure 3 also demonstrates that the accuracy and loss metrics stabilize at consistent values after several iterations of learning when evaluated on the validation dataset.

The performances of the proposed model for automated detection of AF from a single-lead ECG signal are presented in Table 2. When evaluating the test dataset, the proposed model achieved a KP of 0.98, a sensitivity (SE) of 98.6%, a specificity (SP) of 99.3%, a TAC of 99.1%, a positive predictive value (PPV) of 98.8%, and a negative predictive value (NPV) of 99.2%. These results indicate that the proposed model performed exceptionally well in detecting AF.

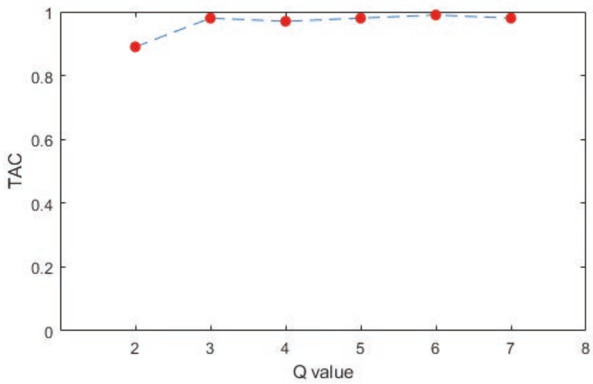

Figure 4. Classification performances when different Q values are applied to MSSelf-ONNs.

In equation (6), Q represents a hyperparameter that governs the level of the Taylor series approximation. Choosing an appropriate Q value will affect the performance of the proposed model, such as accuracy and computational complexity. The best way to find suitable network parameters is literally to perform trial and error tests. To select the appropriate Q value, we have tested the performances of MSSelf-ONN by using different Q values (2, 3, 4, 5, 6, 7). Figure 4 shows the classification performances of the proposed model. From Figure 4, we can conclude that the best Q value is 6. However, when Q is greater than 6, the model has high computational complexity. When q is taken as 3 and 5, the performance of the model remains almost constant. Therefore, according to Figure 4, Q is set to 3.

Table 2. Performance evaluation for the two models.

models	TAC	KP
CNN-3	0.91	0.82
MSSelf-ONN	0.991	0.98

To evaluate the advantages of the proposed model, we conduct a comparative analysis involving MSSelf-ONN with an order of Q=3, the corresponding CNN with an equal number of neurons, and with approximately equivalent network parameters. The corresponding CNN with the same number of parameters are named as CNN-3. Figure 5 shows the network structure of the CNN-3. Table 3 provides the comparison results of the two models. It is observed from Table 3 that the TAC and KP based on the CNN-3 model are 0.91 and 0.82 respectively. This means that the proposed model has a more superior classification ability for AF analysis. The reason why MSSelf-ONN is superior to CNN-3 is that a Self-ONN is characterized by being highly heterogeneous and comprised of generative neurons. This unique composition enables the optimization of the nodal operator function for each kernel element, resulting in Self-ONNs achieving maximum heterogeneity, which enhances both network diversity and learning performance [31]. Consequently, the conventional weight optimization used in traditional CNNs is completely replaced by an operator generation process through optimization techniques. Interestingly, despite the highly nonlinear nature of its kernel elements, each layer of Self-ONN can still be implemented using a single 1-D convolution, facilitating a parallelized implementation similar to that of conventional CNNs.

Table 3. Performance comparison with different kernels.

kernel size	TAC	KP
3 x 1	0.93	0.9
7 x 1	0.94	0.93
15 x 1	0.92	0.91
20 x 1	0.9	0.9
multi-scale kernels	0.991	0.98

In this study, to learn multi-scale feature representation, various multi-scale kernels are used. To verify the effect of multi-scale kernels, we replaced them with different single-scale kernels individually. For Figure 1, we replace multi-scale kernels with 3 x 1, 7 x 1, 15 x 1 and 20 x 1 kernels, respectively. The remaining network structures and parameters remain unchanged. Table 4 presents comparison results of different kernels. From Table 4, we can see that the performance of multi-scale kernels is much better than those of single-scale kernels. According to [8], the disappearance of p-waves and the heart rhythm disorders are the main characteristics of AF. To simultaneously capture these two atrial fibrillation features, it is necessary to set kernels of different scales. The multi-scale kernels should be able to capture temporal patterns at different time scales. Long-term characteristics embody general trends, while short-term characteristics signify delicate fluctuations within specific local areas. Both types of features hold significant potential in enhancing the prediction accuracy for specific tasks.

4.4 Compared With Existing Models

To demonstrate the efficacy of the proposed model in this paper, a comparative analysis is conducted using the MIT-BIH AF database, and the results are presented in Table 5. These studies include the time-frequency analysis time-frequency analysis method proposed by Udawat et al. [19], the different machine learning (ML) algorithms by Jahan et al. [46], deep CNN-LSTM proposed by Petmezas et al. [22] and the network model combining RNN network with CNN proposed by Subramanyan et al. [26]. Based on the data in Table 5, it is evident that Ref. [19] achieved the highest performance, with a SE of 0.988, a TAC of 99.5%, and a SP of 0.992. The exceptional performance can be attributed to the utilization of time-domain, frequency-domain and nonlinear features are extracted from the R-R intervals, which provides promising result. In contrast to MSSelf-ONN, Ref. [19] relies on handcrafted features that necessitate domain knowledge from designers. However, designers often face uncertainty regarding the selection of appropriate handcrafted features from a vast array of options. However, the proposed method is an end-to-end model, which can automatically extract features within its layers from recorded ECG signal. More important, compared with existing deep learning models, the network structure of MSSelf-ONN is very simple. Therefore, this method can be deployed on wearable or portable devices for real-time monitoring of AF. The proposed method serves as a valuable decision-support tool for automated AF detection.

5 Conclusion

In this study, we have introduced an innovative approach for detection AF from ECG recordings, eliminating the need for any handcrafted features. According to Table 2, the proposed model achieves outstanding performance, as reflected by a KP of 0.98, an SE of 0.988, an SP of 0.992, and a TAC of 99.1%. These results provide evidence that both the proposed model and training approach are valuable and successful. The main advantage of the

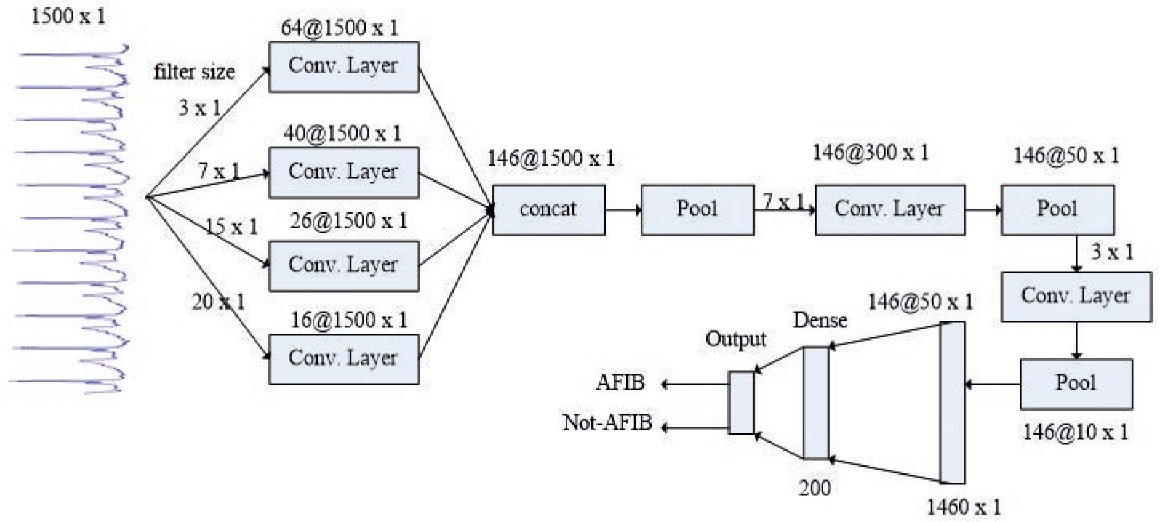

Figure 5. The network structure of CNN-3.

model is the capability of each generative neuron in an operational layer to optimize the nodal operator function of each kernel. This neuron-level heterogeneity contributes to enhancing network diversity and, consequently, improves learning performance. Moreover, the incorporation of a multi-scale signal representation enables a high level of discrimination between normal and arrhythmic ECG signals. Meanwhile, the proposed network complexity is minimized for a real-time application over any platform. It also doesn't require special parallelized hardware. This model can directly implementable on low-power and mobile devices. However, the MSSelf-ONN is very sensitive to signal quality, so it is not suitable for ECG signals with a lot of noise.

From Table 5, we can see that the classification performance of MSSelf-ONNs is not the best. The encouraging outcomes will serve as a driving force for further investigation and exploration. Future endeavors encompass several areas of focus. First, enhancing the classification performance of MSSelf-ONN could involve the incorporation of a recursive operation that leverages contextual information effectively. Second, the classification of ECG signal fragments that encompass multiple classes is another area for exploration. Lastly, evaluating the efficiency of MSSelf-ONNs by applying it to other physiological signals presents another avenue for future research.

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7 Declaration of competing interest

None Declared

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