Arrhythmia Detection from 2-lead ECG using Convolutional Denoising Autoencoders

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ABSTRACT

Cardiac arrhythmia is the cause of death a significant number of deaths. As such, automatic arrhythmia detection from an electrocardiogram (ECG) is an important research topic. There are three difficulties in detecting arrhythmia ECG signals: (1) ECG waveform differences between patients, (2) ECG waveform changes caused by heart rate variability, and (3) observation noise. To address these problems, in several studies, the use of a convolutional neural network (CNN) has been proposed for extracting abstract features from ECG signals. This paper presents a method to classify ECG for arrhythmia detection using a Convolutional Denoising Autoencoder (CDAE). By combining a CNN with a denoising autoencoder (DAE), we expect that more robust features can be extracted. Our ECG classifier is built by combining the encoder part of the CDAE with a fully connected layer. The evaluation results show that the proposed method outperforms the existing works with respect to specific type of arrhythmia (i.e. ventricular ectopic beat, VEB) by 1.3% for sensitivity.

CCS CONCEPTS

• **Applied computing** → **Health care information systems**; • **Information systems** → *Data mining*;

KEYWORDS

Denoising Autoencoders (DAE), Convolutional neural network(CNN), Convolutional Denoising Autoencoders (CDAE), arrhythmia detection from electrocardiogram (ECG)

1 INTRODUCTION

Seven million people from all over the world die annually from cardiac arrhythmia [11, 23], Detecting arrhythmia from electrocardiogram (ECG) readings is clearly an important research topic. There has been substantial research on automatic arrhythmia classification using wavelets [25], filter banks [1], support vector machines [20] and more. Automatic arrhythmia classification from ECG signals can be divided into four steps [14] as follows: (1) ECG signal preprocessing, (2) heartbeat segmentation, (3) feature extraction and (4) learning/classification. In the preprocessing step, noise reduction is applied to ECG signals. Noise reduction methods originated with signal processing techniques, such as the finite impulse response filter[19] and the Kalman filter [18]. The R peak is detected in the segmentation step. Next, features for classification are extracted from the ECG signals in the RR interval (RRI). Finally, arrhythmia classification is performed on the features extracted in previous step. Due to the fact that heartbeat segmentation methods have been well studied and have achieved high levels of accuracy (> 99%), the key steps for improving the classification performance are improved noise reduction and feature extraction [14, 29]. In previous studies, feature extraction was performed by computing handcrafted features, such as signal processing-based frequency characteristics (e.g. wavelet transform [25] or filter bank [1]) and higher order statistics [20]. Recently, techniques for feature extraction from ECG signals using a convolutional neural network (CNN) were proposed and achieved a high performance for arrhythmia detection compared to previous studies [10, 11, 21, 22, 29].

Existing studies can be divided into two categories: the patient-specific approach and the non-patient-specific approach. In the patient-specific approach, there is a patient overlap between training and test (prediction target) data. On the other hand, there is no patient overlap between training and test data in the non-patient-specific approach. Real-world setting applications of the patient-specific approach are very limited because it is difficult to obtain manually annotated ECG data for any specific patient. Thus, non-patient-specific arrhythmia classification is important for a wide variety of applications, and hence it is a challenging problem for the three reasons described below [29].

(1) ECG Waveform Difference between Patients
Due to the fact that ECG waveforms may vary between patients, it is difficult to robustly detect arrhythmia for all patients.

(2) ECG Waveform Changes Caused by Heart Rate Variability
ECG waveforms can change depending on the physiological and mental status of the patient and, thus, are influenced by, for example, stress state, excitement, and exercise. Therefore, it is hard to robustly detect arrhythmia for various patient's statuses.

(3) Observation Noise
ECG signals contain noise caused by the features of the environment, such as electrical noise and the patientsâĂŹ physical movements during ECG measurements. Thus, for appropriate classification, noise reduction is needed.

In several studies, non-patient-specific arrhythmia detection has been examined using a CNN. For example, Rajpurkar et al. [22] built a large-scale dataset of 30,000 unique patients, for arrhythmia detection. Their database had more than 500 times as many entries as the MIT-BIH Arrhythmia Database which is the most widely used, publicly available dataset for performance evaluation of ECG

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classification [22]. Rajpurkar et al. collected single-lead ECG data from a pool of nearly 30,000 patients who used the Zio Patch monitor provided by iRhythm Technologies[1]. In addition to building this large-scale dataset, they proposed a 34-layer CNN model to classify 13 classes of arrhythmia. Their large-scale dataset and deep architecture helped extract high-level (abstract) features, which are important for high-accuracy classification from ECG signals. However, it is very expensive to collect annotated data on such a large scale.

An autoencoder (AE) [8] is used to extract high-level representation of data in the field of image recognition. A Denoising Autoencoder (DAE), which can extract more robust features compared to AE by adding noise to the input data, has been proposed by Vincent et al. [26]. We leveraged the characteristics of both of these AE neural networks for feature extraction from ECG signals.

In this paper, we present a method for non-patient-specific arrhythmia detection that uses a convolutional denoising autoencoder (CDAE). Due to the fact that ECG waveform differences between patients and observation noise complicate the arrhythmia classification from ECG signals, we combine a CNN with a DAE to extract robust features from ECG signals. By adding a fully connected layer to the encoder part of the pretrained CDAE model, we can fine-tune classification model that is highly accurate for new patients. In addition, in the hopes of improving the accuracy of arrhythmia classification by considering the interinfluence characteristics of multichannel ECG, we evaluate 1D and 2D CNN filters for arrhythmia classification.

Our contributions are as follows:

- We present a novel approach for feature extraction and noise reduction for ECG classification using CDAE.
- We evaluate the effectiveness of a DAE for ECG classification using a publicly available ECG dataset.
- With our CDAE model, we achieved the highest sensitivity and specificity of detection for a specific type of arrhythmia (ventricular ectopic beat, VEB) in the MIT-BIH Arrhythmia Database.

The rest of this paper is organized as follows. In Section 2, we review the previous work. Section 3 describes the proposed method. In Section 4, we conduct an experiment on a public dataset and compare the proposed method with existing works. Finally, we conclude the paper and discuss future work in Section 5.

2 RELATED WORK

Over at least the past decade, researchers have developed several techniques to detect arrhythmia from ECG signals. We will first introduce the general framework for arrhythmia detection from ECG signals. Next, we will review previous work on automatic arrhythmia detection.

2.1 Arrhythmia Detection from ECG

ECG signals represent the cardiac electrical activity. For the diagnosis of arrhythmia and other forms of heart diseases, the heart rate, rhythm, and change in each waveform pattern of an ECG are observed. Figure 1 shows an example of a 2-lead ECG from the MIT-BIH Arrhythmia Database [17] The peak of an ECG waveform is called an R-peak, and the interval between two R-peaks is called the RR interval (RRI) as illustrated in Figure 1. An ECG signal is divided into windows, each of which includes signals on both the right and the left sides of the R-peak. Then, for each window, it is decided whether it is arrhythmia or not based on features extracted from each window. Therefore, it is necessary for ECG classification to extract effective features from each window.

[1] http://irhythmtech.com/

2.2 Related Work for Arrhythmia Detection from ECG

As mentioned in Section 1, the state of the art in arrhythmia detection comes from a deep-learning-based approach (e.g., the use of CNNs), which outperforms the handcrafted feature-based approach. Therefore, in this subsection, we review studies that employ deep learning in addition to Rajpurkar et al. [22] described in Section 1. Kiranyaz et al. [10] proposed a method for patient-specific ECG classification using 1D CNN. The model was evaluated on the MIT-BIH Arrhythmia Database and focused primarily on two specific types of arrhythmia: VEB and supraventricular ectopic beat (SVEB). Kiranyaz et al. [11] also proposed a personalized monitoring system. In [11], the classification model was trained by real normal beats and synthesized abnormal beats for binary (i.e. normal class/abnormal class) classification. Since the target of their system was healthy subjects, no real abnormal beats were used in the training datasets. Zubair et al. [29] proposed a method for non-patient-specific ECG classification using 1D CNN. The model that they proposed was comprised of three convolutional layers, three pooling layers and one fully connected layer with Softmax. The performance of the model was evaluated on the MIT-BIH Arrhythmia Database, and its overall accuracy is 92.7%. However, this evaluation is not strictly non-patient-specific because there is a patient overlap between training and test data in this evaluation. In addition, while they

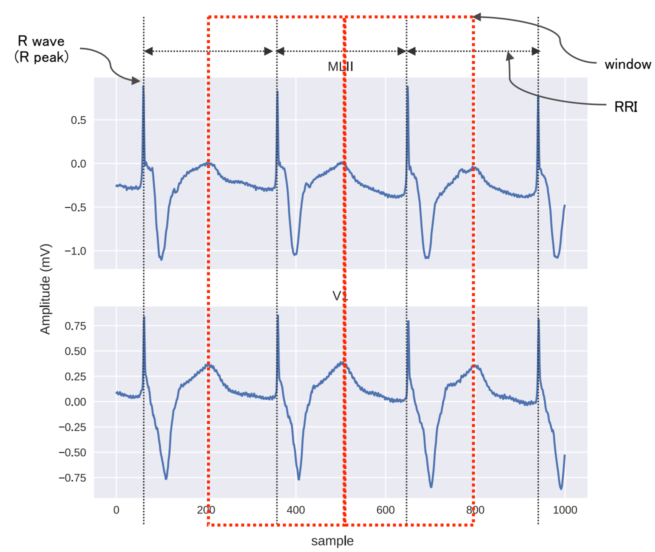

Figure 1: Example of ECG

evaluated the overall accuracy, the classification performance for specific types of arrhythmia was not evaluated. Pourbabaee et al. [21] proposed a five-layer CNN for specific arrhythmia detection (Paroxysmal Atrial Fibrillation, PAF). This method classifies subjects as "health" or "has PAF." They evaluated their method on the PAF prediction challenge dataset[16]. Rahhal et al. [2] proposed to use a stacked denoising autoencoder (SDAE) for active-learning-based classification.

To the best of our knowledge, our work differs from the previously proposed methods in following aspects:

- Although deep CNN and SDAE have been used in existing work, our research is the first to incorporate DAE into the CNN model for ECG classification.
- No existing work evaluated the effect of CNN and DAE for a specific type of arrhythmia in the non-patient-specific approach.

3 THE PROPOSED METHOD

We propose a method for feature extraction from ECG data using CDAEs and arrhythmia classification. The proposed method is divided into two steps as follows: In this paper, we refer to the patient that is not contained in the training data. as the "unseen patient."

i) **Feature Extraction using CDAE (Pretraining)**
DAEs are considered effective for high-level feature representation because ECG signals exhibit a variation that is dependent on the individual patient and observation noise. In addition, since ECG signals are a form of time-series data and it is useful to exploit the data around (both before and after) the classification target, we use a CNN model to extract features from around the classification target [28]. Therefore, we propose to use CDAE, which combines a DAE with a CNN for feature extraction. Similar to a DAE, a CDAE is an unsupervised deep neural network trained so as to reconstruct input data that has been corrupted by adding noise.

ii) **Training Classifier (Fine-Tuning)**
To build our classifier, the encoder part of the CDAE is combined with the fully connected layer for classification. Then, the weights can be fine-tuned using back-propagation. The way of training the weight is similar for the DAE.

In the rest of this section, we will describe the details of each step.

3.1 Feature extraction using CDAE (pre-training)

AEs are a dimensionality reduction algorithm that was proposed by Hinton et al. [8]. The weight of the AE is trained through a multilayer neural network with a small central layer used to reconstruct the input data, which is of high dimensionality. As a result of the training, we can obtain a higher-level representation of the input data. An AE takes an input $\boldsymbol{x} \in \mathbb{R}^d$ and maps it to the hidden representation $\boldsymbol{y} \in \mathbb{R}^{d'}$ using a deterministic mapping function, called the encoder, $\boldsymbol{y} = f_\theta(x) = \sigma(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b})$ with parameterized by $\theta = \{\boldsymbol{W}, \boldsymbol{b}\}$. Here, $\boldsymbol{W}$ is $d \times d'$ weight matrix, $\boldsymbol{b}$ is bias vector and $\sigma(\cdot)$ is an activation function. Let $\boldsymbol{z} \in \mathbb{R}^d$ be reconstructed vector. Then, reverse mapping function, called the decoder, is $z = g_{\theta'}(y) = \sigma(\boldsymbol{W'}\boldsymbol{y} + \boldsymbol{b'})$ with parameterized by $\theta' = \{\boldsymbol{W'}, \boldsymbol{b'}\}$. The weight parameter is usually constrained by $\boldsymbol{W'} = \boldsymbol{W}^T$. Each training datum $\boldsymbol{x_i}$ is then mapped to the corresponding $\boldsymbol{y_i}$ and its reconstruction z_i. The parameters of the AE can be obtained by minimizing the following objective function.

$$\begin{aligned} \theta, \theta' &= \underset{\theta,\theta'}{\arg\min} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{x}_i, \boldsymbol{z}_i) \\ &= \underset{\theta,\theta'}{\arg\min} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{x}_i, g_{\theta'}(f_\theta(\boldsymbol{x}_i))) \end{aligned} \tag{1}$$

where L is a cost function,, for which we will use the mean squared error (MSE): $L(\boldsymbol{x}_i, \boldsymbol{z}_i) = \|\boldsymbol{x}_i - \boldsymbol{z}_i\|^2$.

The DAE proposed by Vincent et al. [26] can extract more robust features compared to the AE algorithm by adding noise to the input data. Figure 2 shows an example of a DAE. In the DAE, the initial input $\boldsymbol{x}$ is corrupted to $\tilde{\boldsymbol{x}}$ by a stochastic mapping $\tilde{\boldsymbol{x}} \sim C(\tilde{\boldsymbol{x}}|\boldsymbol{x})$, which partially destroys the input data. The algorithm uses the corrupted $\tilde{\boldsymbol{x}}$ as input data and then maps it to the corresponding $\boldsymbol{y_i}$ and ultimately to its reconstruction $\boldsymbol{z_i}$. The parameters of DAE can be trained by minimizing the following objective function.

$$\begin{aligned} \theta, \theta' &= \underset{\theta,\theta'}{\arg\min} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{x}_i, \boldsymbol{z}_i) \\ &= \underset{\theta,\theta'}{\arg\min} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{x}_i, g_{\theta'}(f_\theta(\tilde{\boldsymbol{x}}_i))) \end{aligned} \tag{2}$$

Recently, owing to their high performance, CNNs have received considerable attention in the field of image recognition [12] and natural language processing [9, 27] etc. CNNs consist of three basic layers: a convolutional layer, a pooling layer and a classification layer [13]. Features whose patterns appear in the input data are extracted using the convolutional layer, and the pooling layer offers a model that is robust to the location of the patterns appearing in the input data [24]. Only the convolutional layer and the pooling layer are used in the pretraining phase.

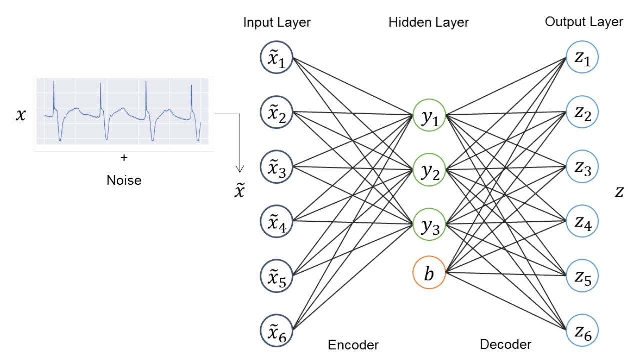

Figure 2: Example of denoising autoencoder

Masci et al. [15] proposed a a convolutional autoencoder (CAE) that uses CNNs in the encoder layer and in the hidden layer of the AE. The difference between the CAE and the AE is weight sharing. The CAE has fewer parameters than the AE. The experimental results showed that the CAE outperforms CNN in several image classification tasks. Du et al. [5] presented stacked convolutional denoising autoencoders (SCDAEs), which are constructed by stacking DAEs whose weights are trained in a convolutional way. Evaluation on large-scale image datasets showed that SCDAE is superior in terms of learning robustness and abstract features.

In this research, we propose to use CDAE which has a convolutional layer and a pooling layer in the encoder and decoder of the DAE for feature extraction. As mentioned in Section 1, there are three problems in arrhythmia detection from ECG signals: ECG waveform change due to patients and heart rate variability, and observation noise. By exploiting the nature of high-level (abstract) features extracted by the convolutional layer and translation-invariant features extraction by the pooling layer, it is possible to extract robust features against patient and heart rate variability. In addition, feature extraction that is robust to observation noise can be performed by adding noise to input data.

For each ECG channel input $\boldsymbol{x}$, the hidden representation $\boldsymbol{y}$ of the kth feature map is represented by

$$\boldsymbol{y}^k = \sigma(\boldsymbol{W}^k * \boldsymbol{x} + \boldsymbol{b}^k) \tag{3}$$

where $*$ denotes the convolutional operation [15]. If the input data is 2-lead (channel) ECG signal, the 2D filter is applied in the convolutional operation. The decoder is denoted by

$$\boldsymbol{z} = \sigma(\sum_{k \in H} \boldsymbol{W}'^k * \boldsymbol{y}^k + \boldsymbol{b}'^k) \tag{4}$$

where H indicates the group of latent feature maps. We use the MaxPooling as the pooling layer in the encoder, and we use Upsampling in the decoder. MaxPooling outputs the maximum value within the region covered by the filter. Upsampling repeats (copies) the input value up to the filter size. Let $\tilde{\boldsymbol{x}}_i$ and $\boldsymbol{z}_i$ be the corrupted input data and the output data, respectively. Then, the loss function is represented as in Eq. (2). Equation (2) is optimized using a back-propagation algorithm.

3.2 Building Classifier (Fine-Tuning)

CDAEs have no classification function. To build an arrhythmia classifier, a fully connected layer (classification layer) is added on top of the encoder part of the CDAE described in Section 3.1. Figure 3 presents a conceptual depiction of building the classifier from a pretrained CDAE model. The weights and the neural network architecture are extracted from the pretrained CDAE model, and the fully connected layer is added as an output layer. The number of units of the output layer is the number of classes into which we would like to classify arrhythmia. The classifier is trained by supervised learning using input data $\boldsymbol{x}$ and an annotated label as an output.

The Softmax function is used as an activation function for the output layer of the classifier. By using the Softmax function, the output of each unit can be treated as the probability of each label. Here, let N be the number of units of the output layer, let $\boldsymbol{x}$ be the input, and let $\boldsymbol{x}_i$ be the output of unit i. Then, the output $p(i)$ of unit i is defined by the following equation.

$$p(i) = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \tag{5}$$

Cross-entropy is used as the loss function of classifier L_{CLF} as follows.

$$L_{CLF}(\theta) = -\frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} log(p_{ij}) \tag{6}$$

where n is the sample size, m is the number of classes, p_{ij} is the output of the classifier of class j of the ith sample and y_{ij} is the annotated label of class j of the ith sample.

4 EXPERIMENTS

4.1 Experimental Setting

We used the MIT-BIH Arrhythmia Database[2] which is the most widely used database in existing ECG classification [14] for performance evaluation. This database contains 48 records, each containing 2-lead ECG signals for a 30 min segment from a 24 h recording. Each ECG signal is bandpass-filtered at 0.1 - 100 Hz and the sampling frequency is 360Hz. The 44 records except for 102, 104, 107, 217 from MIT-BIH Arrhythmia Database are selected for the experiment because these excluded records do not have sufficient signal quality based on Association for the Advancement of Medical Instrumentation (AAMI)[3] recommendation [6]. This same criterion is used in existing work such as [10, 29]. Each record has RRI and annotated labels provided by PhysioNet. The AAMI recommends that each ECG beat be classified into the following five heartbeat types: N (normal beats), S (supraventricular ectopic beats, SVEB), V (ventricular ectopic beats, VEB), F (fusion beat), and Q (unclassifiable beats).

[2] https://physionet.org/physiobank/database/mitdb/
[3] http://www.aami.org

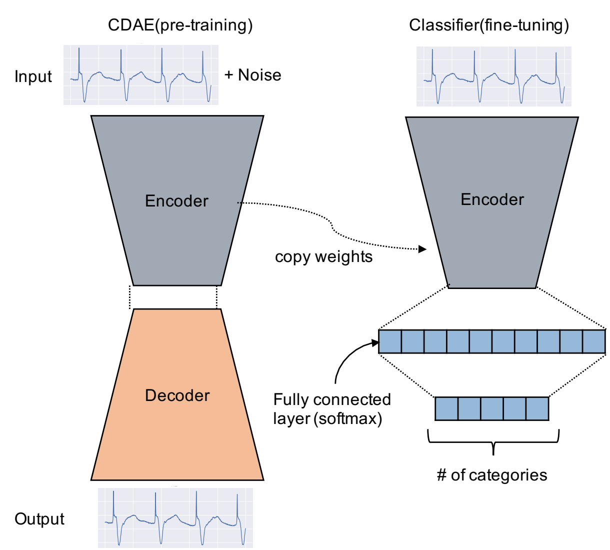

Figure 3: Fine-tuning of classifier

Each window of an ECG waveform has a different size because the RRI is not constant. In addition, the ECG of each patient has a different amplitude. Therefore, we normalized ECG signals. To standardize the length of the RRI of each window, the data is resampled at a fixed rate using a Fourier transform. Next, the amplitude of each window is normalized from 0 to 1. In our setting, the normalization is applied after resampling at a fixed rate of 160 samples from each window.

To evaluate the performance of the classification of unseen patients, we conducted a 5-fold cross-validation. Specifically, we divided the 44 users into five groups. The model was trained by the data of four groups, and a test was conducted on the remaining group. We repeatedly changed the group used for testing five times, in conducting 5-fold Leave-One-Group-Out Cross-Validation. 5,000 beats were randomly sampled from the training data as validation data. These validation data were then removed from the training data. Table 1 shows an example of AAMI recommended classes of arrhythmia and the number of samples in training and test set from one-fold.

Classification performance is measured by using the following four metrics in the literature [10]. Classification Accuracy (*Acc*), Sensitivity (*Sen*), Specificity (*Spe*), and Positive Predictive Value (*Ppv*). While accuracy can be used for evaluating the overall performance, the other metrics can measure the performance of specific class. These four metrics are defined by following numbers: true positive (*TP*), true negative (*TN*), false positive (*FP*) and false negative (*FN*). *Accuracy* is the ratio of the number of correctly classified samples to the total number of samples. *Acc = (TP + TN)/(TP + TN + FP + FN). Sensitivity* is the ratio of positives that are correctly classified to actually positive samples. *Sen = TP/(TP + FN). Specificity* is the ratio of negatives that are correctly classified to actually negative samples. *Spe = TN/(TN + FP). Positive Predictive Value* is the ratio of the number of correctly classified positive samples to the number of the samples which is predicted as positive. *Ppv = TP/(TP + FP).*

Table 2 shows the architecture of the CDAE used in our evaluation. We used three convolution layers and three pooling layers in CDAE. ReLU [7] is used as the activation function and Nadam [4] is used as the optimization method. The initial learning rate is set to 0.002 and gradually decreased. The input data is corrupted by Gaussian distribution (mean=0, std=0.001).

The classifier is constructed by combining the pretrained encoder part of the CDAE with the fully connected layer. We added 32-dimensional and 5-dimensional full connected layers. Figure 4 shows the details of the architecture of the classifier. Cross-entropy was used as the loss function and Stochastic Gradient Descent [3] was used as the optimization method. The initial learning rate was set to 0.01 and gradually decreased.

Table 1: AAMI recommended classes of arrhythmia and number of samples

Label	Description	Count	
		Training	Test
N	Normal beats	67,810	17,792
S	Supraventricular ectopic beats	2,447	178
V	Ventricular ectopic beats	5,013	1,680
F	Fusion beats	726	29
Q	Unknown beats	12	2

4.2 Results

Figure 5 shows the training curve of the CDAE. This figure indicates that the errors of the test data (loss) and validation data (val-loss) decrease by increasing the epoch. The result shows that CDAEs can extract high-level features not only from the training data but also from unseen data. Figure 6 shows two examples (blue and green lines) of ECG signals reconstructed ECG signals from the test data using the CDAE. The reconstructed waveform shows the effect of denoising while maintaining its overall shape.

Figure 7 shows the learning curve of the classifier, and Figure 8 shows the accuracy of each epoch. The errors of the test data (loss) and the validation data (val-loss) decrease by increasing epochs, similar to pretraining. The accuracy increases with the epoch.

The evaluation results are shown in Table 3 for Type V (VEB) and in Table 4 for Type S (SVEB). Since the overall accuracy is dominated by normal beats, we evaluated a specific type of arrhythmia. Table 5 shows the confusion matrix of the proposed method. Due to the fact that there is no existing work using the MIT-BIH Arrhythmia Database for specific types of arrhythmia with the non-patient-specific approach, we compared the proposed method with a similar CNN model proposed in the work of Zubair et al. [29] as a baseline method. The difference between their CNN model and the proposed model is the incorporation of a DAE. In addition, we evaluated the effect of 1D and 2D CNN filters on arrhythmia classification.

From Table 3, we can see that the proposed method with the 2D convolution filter is the model with best performance. While the performance of the 2D convolution filter is higher than that of the 1D filter for all metrics in the proposed method, the trend in the baseline method (Zubair et al. [29]) that we used for our comparison is different. Regarding sensitivity, which is the most important metric for arrhythmia detection, the proposed method with the 2D filter outperforms the baseline method with the 1D filter by 1.3%. From Table 4, the proposed method with the 2D filter

Table 2: Architecture of the CDAE

	Layer	Type	Shape	Activation
Encoder	0	Noise	(160, 2)	
	1	Conv1D	(160, 32)	ReLU
	2	MaxPooling	(80, 32)	
	3	Conv1D	(80, 16)	ReLU
	4	MaxPooling	(40, 16)	
	5	Conv1D	(40, 4)	ReLU
	6	MaxPooling	(20, 4)	
Decoder	7	UpSampling	(40, 4)	
	8	Conv1D	(40, 16)	ReLU
	9	UpSampling	(80, 16)	
	10	Conv1D	(80, 32)	ReLU
	11	UpSampling	(160, 32)	
	12	Conv1D	(160, 2)	ReLU

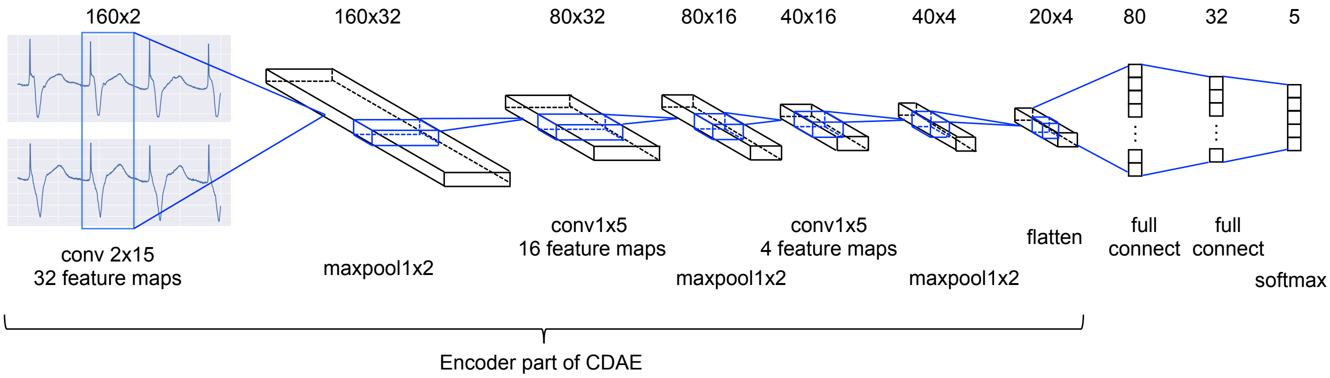

Figure 4: Architecture of the classifier

has the highest accuracy and specificity, whereas the proposed method with the 1D filter has the highest sensitivity and positive predictive value for SVEB. However, the sensitivity and positive predictive value for SVEB are quite low, which is a limitation of the proposed method. The reason might be that the set of training samples of Type S was small. We would like to clarify the effect of sample size on the classification accuracy in the future work.

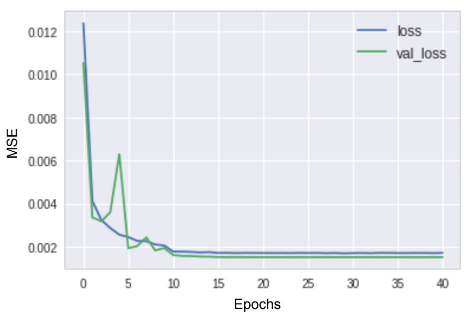

Figure 5: Learning Curve of CDAE

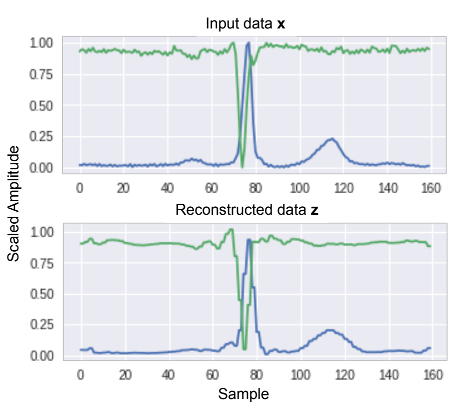

Figure 6: Example of the reconstructed data using CDAE

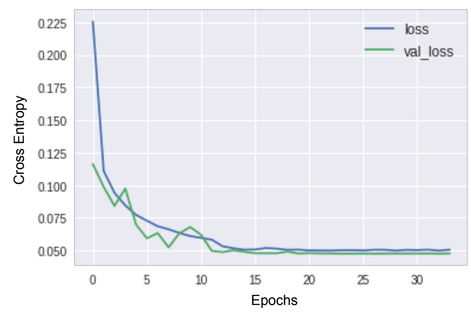

Figure 7: Learning curve of classifier

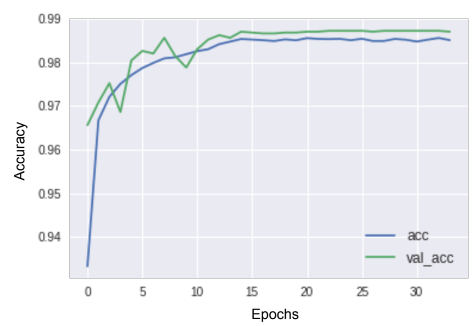

Figure 8: Accuracy of classifier

5 CONCLUSION

In this paper, we proposed a method for arrhythmia detection from ECG signals using a Convolutional Denoising Autoencoder. While the CNN-based approach has been already proposed, this research is the first to incorporate a DAE with a CNN for arrhythmia detection. The weight of the neural network is trained by the CDAE, and the classifier is built by combining the encoder part of the CDAE with a fully connected layer. The evaluation results show that the CDAE is effective for VEB in the non-patient-specific approach for arrhythmia diagnosis.

In the future work, we would like to investigate the effect of the size of the training data on the classification performance to improve the classification accuracy of SVEB. In addition, we would like to apply the proposed method to not only 2-lead ECGs but also 12-lead ECGs which are widely used in the clinical field. While the 12-lead ECG has a vast amount of information and spatially helpful data compared to 2-lead ECG, there is a limit in visual examination by cardiologists because there is so much information. Therefore, we expect automatic arrhythmia detection to be an efficient means of diagnosis in this case, as well.

REFERENCES

[1] Valtino X Afonso, Willis J Tompkins, Truong Q Nguyen, and Shen Luo. 1999. ECG beat detection using filter banks. *IEEE transactions on biomedical engineering* 46, 2 (1999), 192–202.

[2] MM Al Rahhal, Yakoub Bazi, Haikel AlHichri, Naif Alajlan, Farid Melgani, and RR Yager. 2016. Deep learning approach for active classification of electrocardiogram signals. *Information Sciences* 345 (2016), 340–354.

[3] Léon Bottou. 2010. Large-scale machine learning with stochastic gradient descent. In *Proceedings of COMPSTAT'2010*. Springer, 177–186.

[4] Timothy Dozat. 2015. *Incorporating Nesterov momentum into Adam.* Technical Report. Stanford University, Tech. Rep., 2015.[Online]. Available: http://cs229. stanford. edu/proj2015/054 report. pdf.

[5] B. Du, W. Xiong, J. Wu, L. Zhang, L. Zhang, and D. Tao. 2017. Stacked Convolutional Denoising Auto-Encoders for Feature Representation. *IEEE Transactions on Cybernetics* 47, 4 (April 2017), 1017–1027.

[6] Association for the Advancement of Medical Instrumentation. Arrhythmia Monitoring Subcommittee. 1986. *Recommended Practice for Testing and Reporting Performance Results of Ventricular Arrhythmia Detection Algorithms (proposed).* Association for the Advancement of Medical Instrumentation.

[7] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. 2011. Deep Sparse Rectifier Neural Networks.. In *Aistats*, Vol. 15. 275.

[8] Geoffrey E Hinton and Ruslan R Salakhutdinov. 2006. Reducing the dimensionality of data with neural networks. *science* 313, 5786 (2006), 504–507.

[9] Yoon Kim. 2014. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882* (2014).

[10] Serkan Kiranyaz, Turker Ince, and Moncef Gabbouj. 2016. Real-time patient-specific ECG classification by 1-D convolutional neural networks. *IEEE Transactions on Biomedical Engineering* 63, 3 (2016), 664–675.

[11] Serkan Kiranyaz, Turker Ince, and Moncef Gabbouj. 2017. Personalized Monitoring and Advance Warning System for Cardiac Arrhythmias. *Scientific Reports* 7, 1 (2017), 9270.

[12] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*. 1097–1105.

[13] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. 1998. Gradient-based learning applied to document recognition. *Proc. IEEE* 86, 11 (1998), 2278–2324.

[14] Eduardo José da S Luz, William Robson Schwartz, Guillermo Cámara-Chávez, and David Menotti. 2016. ECG-based heartbeat classification for arrhythmia detection: A survey. *Computer methods and programs in biomedicine* 127 (2016), 144–164.

Table 3: Classification performance for VEB

Method	Filter	*Acc*	*Sen*	*Spe*	*Ppv*
Zubair et al. [29]	1D	0.951	0.834	0.961	0.719
Zubair et al. [29]	2D	0.947	0.771	0.962	0.771
Proposed	1D	0.951	0.801	0.964	0.740
Proposed	2D	**0.957**	**0.847**	**0.966**	**0.748**

Table 4: Classification performance for SVEB

Method	Filter	*Acc*	*Sen*	*Spe*	*Ppv*
Zubair et al. [29]	1D	0.939	0.117	0.966	0.108
Zubair et al. [29]	2D	0.962	0.153	0.988	0.231
Proposed	1D	0.947	**0.154**	0.971	**0.234**
Proposed	2D	**0.966**	0.048	**0.993**	0.214

Table 5: Classification result of test data

Label	Classification result				
	N	S	V	F	Q
N	17,594	105	40	53	0
S	127	29	17	5	0
V	203	39	1,438	0	0
F	27	1	1	0	0
Q	1	0	1	0	0

[15] Jonathan Masci, Ueli Meier, Dan Cireşan, and Jürgen Schmidhuber. 2011. Stacked convolutional auto-encoders for hierarchical feature extraction. *Artificial Neural Networks and Machine Learning–ICANN 2011* (2011), 52–59.

[16] George Moody, A Goldberger, S McClennen, and S Swiryn. 2001. Predicting the onset of paroxysmal atrial fibrillation: The Computers in Cardiology Challenge 2001. In *Computers in Cardiology 2001*. IEEE, 113–116.

[17] George B Moody and Roger G Mark. 2001. The impact of the MIT-BIH arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine* 20, 3 (2001), 45–50.

[18] S.J. Orfanidis. 1988. *Optimum signal processing: an introduction.* Macmillan.

[19] Sophocles J. Orfanidis. 1995. *Introduction to Signal Processing.* Prentice-Hall, Inc., Upper Saddle River, NJ, USA.

[20] Stanislaw Osowski, Linh Tran Hoai, and Tomasz Markiewicz. 2004. Support vector machine-based expert system for reliable heartbeat recognition. *IEEE transactions on biomedical engineering* 51, 4 (2004), 582–589.

[21] Bahareh Pourbabaee, Mehrsan Javan Roshtkhari, and Khashayar Khorasani. 2017. Deep Convolutional Neural Networks and Learning ECG Features for Screening Paroxysmal Atrial Fibrillation Patients. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (2017).

[22] Pranav Rajpurkar, Awni Y Hannun, Masoumeh Haghpanahi, Codie Bourn, and Andrew Y Ng. 2017. Cardiologist-level arrhythmia detection with convolutional neural networks. *arXiv preprint arXiv:1707.01836* (2017).

[23] Yoram Rudy. 2010. Noninvasive imaging of cardiac electrophysiology and arrhythmia. *Annals of the New York Academy of Sciences* 1188, 1 (2010), 214–221.

[24] Dominik Scherer, Andreas Müller, and Sven Behnke. 2010. Evaluation of pooling operations in convolutional architectures for object recognition. *Artificial Neural Networks–ICANN 2010* (2010), 92–101.

[25] VK Srivastava and Devendra Prasad. 2013. DWT-Based Feature Extraction from ecg Signal. *American J. of Eng. Research (AJER)* 2, 3 (2013), 44–50.

[26] Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. 2008. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th international conference on Machine learning*. ACM, 1096–1103.

[27] Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In *Advances in neural information processing systems*. 649–657.

[28] Yi Zheng, Qi Liu, Enhong Chen, Yong Ge, and J Leon Zhao. 2014. Time series classification using multi-channels deep convolutional neural networks. In *International Conference on Web-Age Information Management*. Springer, 298–310.

[29] Muhammad Zubair, Jinsul Kim, and Changwoo Yoon. 2016. An Automated ECG Beat Classification System Using Convolutional Neural Networks. In *6th International Conference on IT Convergence and Security (ICITCS)*. IEEE, 1–5.