Computer Engineering and Applications Vol. 11, No. 1, February 2022

Inter Patient Atrial Fibrillation Classification Using One Dimensional Convolution Neural Network

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ABSTRACT

Atrial fibrillation is the most common type of arrhythmia. The process of detecting AF disease is quite difficult. This is because it is necessary to detect the presence or absence of a P signal wave in the ECG signal. However, this method requires special expertise from a cardiologist. Several literatures have proposed an automatic ECG classification system. However, the intra-patient paradigm does not simulate real-world scenarios. One of the challenges in the inter-patient paradigm is the morphological differences between one subject and another. In order to overcome the problems that arise in the automatic classification of ECG signal patterns a deep learning approach was proposed. This study proposes the classification process of atrial fibrillation in the inter-patient paradigm using a one-dimensional convolutional neural network architecture. The test is divided into two cases: two labels (Normal and AF) and three labels (Normal, AF and Non-AF). In the case of two test labels with an inter-patient scheme, the performance was 100% for all test metrics (accuracy, sensitivity, precision, and F1-Score). However, in the three-label case, the model's performance decreased to 85.95, 70.02, 72.50, 71.19 for accuracy, sensitivity, precision and F1-Score, respectively.

Keywords: Atrial Fibrillation, One Dimensional Convolutional Neural Network, Inter-patient Scheme.

1. INTRODUCTION

Atrial fibrillation is the most common type of arrhythmia. Atrial fibrillation occurs when the muscle in the heart malfunctions and causes an irregular heartbeat, an irregular heartbeat can form blood clots in the chambers of the heart and inhibit the blood circulation process so that it becomes a factor in the emergence of cardiovascular disorders.

Several literatures have proposed an automatic ECG classification system. In [1] and [2], for example, the authors tried to classify ECG signals using the intra-patient paradigm using artificial neural networks and support vector machines. However, the intra-patient paradigm does not simulate real-world scenarios. This paradigm to classify someone, requires a label from the same person [3]. To overcome this limitation, Chazal et al. [4] proposed an inter-patient paradigm. In this case, one set of patients is separated to build a classification system, and another set of patients is used for testing.

One of the challenges in the inter-patient paradigm is the morphological differences between one subject and another. This morphological difference is caused by several things such as age, diet, sleeping habits, etc. Furthermore, the

difference in sampling frequency on the electrocardiogram machine and the effect of noise during data recording add to the difficulty of the classification process. One solution to overcome the problems that arise in the automatic classification of ECG signal patterns is to use a deep learning approach.

Based on research that has been done in the last few years, deep learning has succeeded in classifying with a high level of accuracy [5]. Several deep learning methods are used to classify AF, including Deep Neural Networks (DNN) [6], Deep Belief Network (DBN) [7], Recurrent Neural Networks (RNN) [8], and Convolutional Neural Networks (CNN). [9]. The deep learning method proposed in this research is Convolutional Neural Networks (CNN). This is because CNN has the advantage of combining feature extraction and classification in a learning process. Therefore, CNN can directly process the ECG signal without any pre-processing of data, such as feature extraction, feature selection, feature dimension reduction, and others [10]. In addition, the advantages of CNN can produce discriminatory features directly from the data or feature learning [11]. With these discriminatory features, it is hoped that this research can classify well and get a high level of accuracy.

This study proposes the classification process of atrial fibrillation in the inter-patient paradigm using a one-dimensional convolutional neural network architecture. The remainder of this paper is structured as follows. Section 2 describes the materials and methods used in the study. Section 3 explains the result of the proposed method and discussion. Finally, Section 4 concluded the findings of the paper.

2. MATERIAL AND METHODS

2.1 MATERIAL

In this study, we used data from three different datasets, namely the Atrial Fibrillation Challenge [12], China Challenge 2018 [13], and Chapman University and Shaoxing People Hospital [14]. The total data used from these three datasets is 23,710 records. Table 1 shows the distribution of data from the dataset used.

TABLE 1.
Dataset Distribution

Dataset	Class	Sub Class	Record	Training Data	Validation Data	Unseen Data
AF Challenge 2017	AF	-	771			-
	Normal	-	5154			
China Challenge 2018	Normal	-	918	19755	2194	92
	AF	-	1098			110
	Non AF	First-degree atrioventricular block (I-AVB)	704			71
		Left bundle branch block (LBBB)	207			21

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

Dataset	Class	Sub Class	Record	Training Data	Validation Data	Unseen Data
		Right bundle branch block (RBBB)	1695			170
		Premature atrial contraction (PAC)	556			58
		Premature ventricular contraction (PVC)	672			66
		ST-segment depression (STD)	825			83
		ST-segment elevated (STE)	202			21
Chapman University and Shaoxing People Hospital [7]	Normal	-	1826			183
	AF	-	1780			178
	Non AF	Sinus Bradycardia	3889			389
		Sinus Tachycardia	1568			157
		Atrial Flutter	445			45
		Sinus Irregularity	399			40
		Supraventricular Tachycardia	587			59
		Atrial Tachycardia	121			13
		Atrioventricular Node Reentrant Tachycardia	16			2
		Atrioventricular Reentrant Tachycardia	8			1
		Sinus Atrium to Atrial Wandering Rhythm	7			1
	Total			19756	2194	1760

2.2 METHODS

2.2.1 PRE-PROCESSING

In general, the flow of this research is shown in Figure 1. In the pre-processing stage, the three datasets used go through 3 processes which include denoising, normalization and segmentation. In this study, signal denoising was carried out using a transformation (DWT), because the transformation is very efficient in terms of analysis and signal denoising. DWT is used to analyze the signal by splitting the signal at different resolutions. DWT in this study is applied to 8 levels for low pass filter and high pass filter. Figure 2(a) - (c) shows the results of signal denoising.

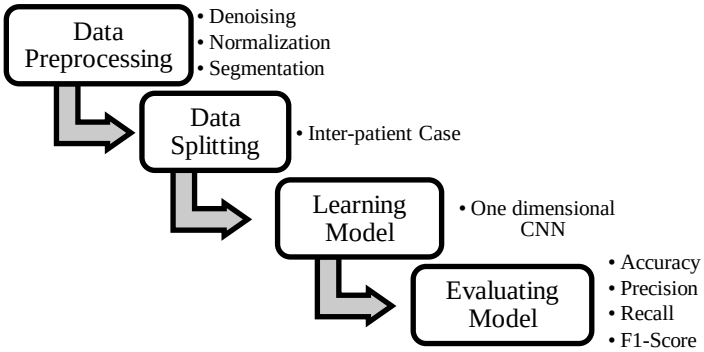
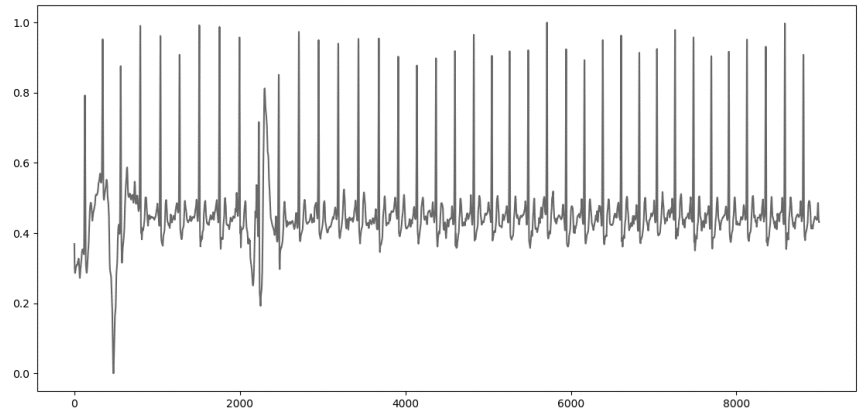
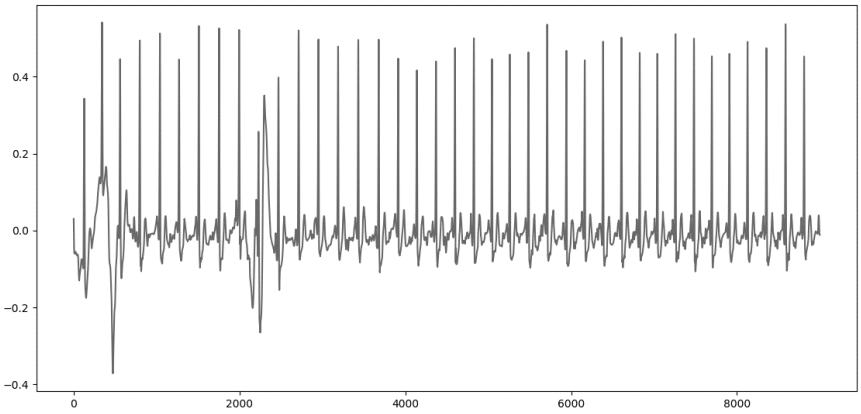


FIGURE 1. Research Methodology



(a)



(b)

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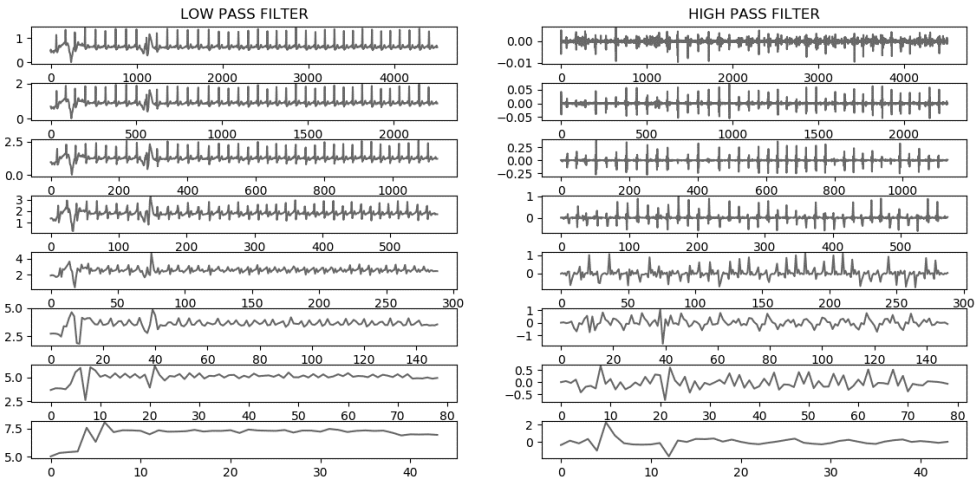
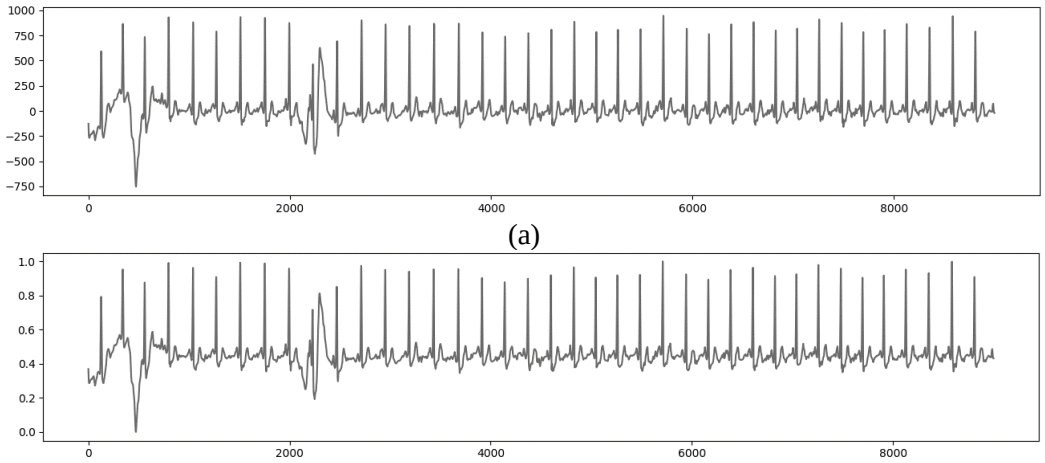
ISSN: 2252-5459 (Online)



(c)

FIGURE 2. (a) Signal before denoising process. (b) Signal after denoising process. (c) Decomposition of 8 Level Low Pass Filter and High Pass Filter of Signal Denoising

The datasets used have different amplitude ranges. Therefore, normalization is needed to overcome this. Signal normalization proposed in this study is in the range of 0-1, with a lower limit of 0 and an upper limit of 1. The comparison of signals before normalization and after normalization can be seen in Figure 3.



(a)

(b)

FIGURE 3. Signal Comparison (a) Before Normalization and (b) After Normalization

The three datasets have different signal lengths, therefore it is necessary to equalize the signal length using segmentation techniques. The segmentation process (signal truncation) is done by selecting the minimum length of the entire data, which is 2700 nodes so that all signals having a length of more than the specified value will be cut. Figure 4 shows the results of signal segmentation of 2700 nodes.

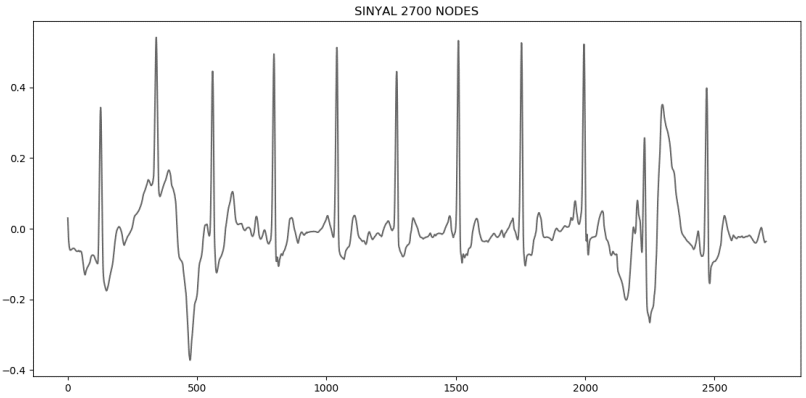


FIGURE 4. Results of 2700 node signal Segmentation.

2.2.2 DATA SPLITTING

After the segmentation process, all the data is split into two sets, namely training and testing. The process of data separation in the inter-patient scenario is divided based on the order of records, so that there is no data from the same patient in the train set and test set. In intra- and inter-patient scenarios, training will be carried out using the k-fold cross validation method with a total of k=10. The training set is used to build a one-dimensional CNN classification model, while the test set is used to evaluate the model from the training results.

2.2.3 ONE DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK

In this study, the classification was carried out using a one-dimensional CNN. The steps taken are by training the training data and then testing it with data testing. The 1-dimensional CNN architecture used in this study includes 13 convolutional layers, two fully connected 1000 nodes each and 1 node for the output layer [8].

2.2.4 EVALUATION METRICS

Evaluation is carried out to determine the accuracy and precision of the model that has been made in classifying, the evaluation will be carried out using test data. The accuracy and accuracy of the model in classifying can be evaluated by calculating AF data detected to AF by the system or True Positive (TP), AF data detected as Normal or False Negative (FN), normal data detected by AF or False Positive (FP), and normal data detected by the system is normal or True Negative (TN). The four values are contained in the confusion matrix Table 2 [27].

TABEL 2.
Confusion Matrix

Confusion Matrix		True Label	
		Negative (0)	Positive (1)
Predicted Label	Negative (0)	TN	FN
	Positive (1)	FP	TP

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

The following performance values can be calculated using *confusion matrix*:

1. Accuracy

Accuracy is a performance value that shows the number of correct predictions from the entire data. However, accuracy cannot be used as a reference for the classification of imbalanced data.

$$Akurasi = \frac{(TP + TN)}{(TP + FN + FP + TN)} \quad (1)$$

2. Precision

Precision is a performance value that shows the number of correct positive data predictions from all positive data predictions.

$$Presisi = \frac{TP}{(TP + FP)} \quad (2)$$

3. Sensitivity

Sensitivity is a performance value that shows the number of truly positive data predictions from all positive data.

$$Sensitivitas = \frac{TP}{(TP + FN)} \quad (3)$$

4. F1 Score

F1 score is the overall performance value that is influenced by precision and sensitivity (equation 3.8). The F1 score will be better if the false positive and false negative values are less. F1 score is needed to classify unbalanced data.

$$F1\ Score = \frac{2(Precision * Sensitivity)}{(Precision + Sensitivity)} \quad (4)$$

3. RESULT AND DISCUSSION

3.1 SCENARIO 1: NORMAL AND AF

In first scenario performance evalution, it was done using normal data and atrial fibrillation. The test is carried out using cross fold validation with a total of k = 10. Table 3 shows the test results using training data in case one using k-fold cross validation.

TABLE 3.
Performance on Test Data

Fold	Accuracy (%)	Sensitivity (%)	Precision (%)	F1 Score (%)
1	100	100	100	100
2	100	100	100	100
3	100	100	100	100
4	100	100	100	100
5	100	100	100	100
6	100	100	100	100
7	100	100	100	100
8	100	100	100	100
9	100	100	100	100
10	100	100	100	100
Average	100	100	100	100

Furthermore, the model was tested using unseen data as shown in Table 4. It can be seen from table 4 that the highest accuracy is obtained at fold 9. Furthermore, the test was continued by using unseen data using two classes, normal and AF. The test results show the value of accuracy, sensitivity, precision and F1 Score of 100% on unseen data. This is because there are no values for False Positive and False Negative as shown in Table 5.

TABLE 4.
Performance on Unseen Data

Fold	Accuracy (%)	Sensitivity (%)	Precision (%)	F1 Score (%)
1	90.94	88.79	85.92	87.22
2	99.75	99.84	99.43	99.63
3	99.24	99.11	98.71	98.90
4	99.75	99.83	99.47	99.65
5	99.87	99.92	99.71	99.81
6	99.87	99.91	99.76	99.84
7	99.87	99.91	99.76	99.84
8	99.75	99.64	99.64	99.64
9	100	100	100	100
10	99.87	99.73	99.92	99.82
Average	98.89	98.67	98.23	98.44

TABLE 5.
Confusion Matrix of Unseen Data

	Normal	AF
Normal	6861	0
AF	0	3188

3.2 SCENARIO 2: NORMAL, AF AND NON-AF (AFL, APB, PVC)

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

In the second case testing was carried out using normal data, atrial fibrillation and Non-AF. Non-AF data is signal data that almost similar with AF such as Atrial Flutter (AFL), Atrial Premature Beat (APB), and Premature Ventricular Contraction (PVC). The results of the Training Model using k-fold cross validation with k = 10 showed in table 6. Moreover, the validation accuracy of each fold is showed in table 7 and it can be inferred that the fifth fold bas the best model with 99.22% for accuracy, 98.12 % for sensitivity, 98.01 for precision and 98.07 for F1-Score. Finally, Table 8 showed the confusion matrix of validation data on fold 5.

TABLE 6.
Performance on Training Data

Fold	Accuracy (%)	Sensitivity (%)	Precision (%)	F1 Score (%)
1	99,61	99.49	99.3409	99.4203
2	99,25	99.52	99.4521	99.4891
3	99,59	99.23	99.2868	99.2611
4	99,62	99.36	99.5496	99.4549
5	99,47	99.46	99.2389	99.3503
6	99,58	99.16	99.4152	99.2887
7	99,62	99.13	99.1563	99.1434
8	99,53	99.43	99.4314	99.4315
9	99,27	99.18	99.5363	99.3614
10	99,53	99.51	99.2716	99.3947
Average	99.507	99.347	99.36791	99.3595

TABLE 7.
Performance on Validation Data

Fold	Accuracy (%)	Sensitivity (%)	Precision (%)	F1 Score (%)
1	82,88	68.47	70.13	68.88
2	93,26	92.50	91.99	92.24
3	97,76	88.79	93.28	90.77
4	98,76	97.66	97.56	97.61
5	99,22	98.12	98.01	98.07
6	98,86	98.35	98.32	98.34
7	99,13	98.70	98.92	98.81
8	97,08	97.92	97.93	97.92
9	99,13	98.81	97.88	98.33
10	99,08	98.74	98.00	98.36
Average	96.516	93.806	94.202	93.933

TABLE 8.
Confusion matrix validation data on fold 5

	Normal	AF	Non-AF
Normal	761	0	1
AF	3	355	4
Non-AF	2	7	1061

In order to test the level of generalizability of the developed model, the testing was carried out using an inter-patient scheme. In this scheme, the patients used in

the testing data are different from the patients in the training data. This test aims to test the model's performance in real-world cases. This test resulted in accuracy, sensitivity, precision and F1-Score of 85.95, 70.02, 72.50, 71.19 respectively. Table 9 shows the confusion matrix from the unseen test using the best model of the previous result (fold 5). It can be inferred from table 9 that 50% normal label was predicted to Non-AF class. This happens because the Non-AF data is a combination of several signals, causing the pattern of the Non-AF signal to vary greatly.

TABLE 9.
Confusion matrix of unseen data using the best model

	Normal	AF	Non-AF
Normal	138	0	137
AF	13	210	65
Non-AF	98	58	1041

4. CONCLUSION

This study focuses on the classification of normal and AF signals using the Inter-patient paradigm. The inter-patient paradigm is a paradigm that resembles real-world cases. The test is divided into two cases: two labels (Normal and AF) and three labels (Normal, AF and Non-AF). In the case of two test labels with an inter-patient scheme, the performance was 100% for all test metrics (accuracy, sensitivity, precision, and F1-Score). However, in the three-label case, the model's performance decreased to 85.95, 70.02, 72.50, 71.19 for accuracy, sensitivity, precision and F1-Score, respectively. This declaiming is due to the 50% of normal data was predicted as Non-AF label. Several normal data have a similar pattern with Non-AF data because Non-AF data is a combination of several signals so that it has a very varied pattern. In future research, we will try to overcome the similarity of patterns between normal and Non-AF data.

ACKNOWLEDGEMENTS

The research/publication of this article was funded by DIPA of Public Service Agency of Universitas Sriwijaya 2021. SP DIPA-023.17.2.677515 /2021, On November 2020. In accordance with the Rector’s Decree Number: 0023/UN9/SK.LP2M.PT/2021, On July 22, 2021

REFERENCES

[1] İ. Güler and E. D. Übeylı̇, “ECG beat classifier designed by combined neural network model,” *Pattern Recognit.*, vol. 38, no. 2, pp. 199–208, Feb. 2005.
[2] B. M. Asl, S. K. Setarehdan, and M. Mohebbi, “Support vector machine-based arrhythmia classification using reduced features of heart rate variability signal,” *Artif. Intell. Med.*, vol. 44, no. 1, pp. 51–64, Sep. 2008.
[3] E. J. da S. Luz, W. R. Schwartz, G. Cámara-Chávez, and D. Menotti, “ECG-based heartbeat classification for arrhythmia detection: A survey,” *Comput. Methods Programs Biomed.*, vol. 127, pp. 144–164, Apr. 2016.

ISSN: 2252-4274 (Print)
ISSN: 2252-5459 (Online)

[4] P. deChazal, M. O'Dwyer, and R. B. Reilly, "Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1196–1206, Jul. 2004.

[5] S. Khan, H. Rahmani, S. A. A. Shah, and M. Bennamoun, *A Guide to Convolutional Neural Networks for Computer Vision*, vol. 8, no. 1. 2018.

[6] S. Hong *et al.*, "ENCASE : an ENsemble ClASsifiEr for ECG Classification Using Expert Features and Deep Neural Networks," vol. 44, pp. 2–5, 2017.

[7] R. Tripathy, M. R. Arrieta Paternina, J. G. Arriaeta, P. Pattanaik, and G. € Sanatorio, "Automated Detection of Atrial Fibrillation Ecg Signals Using Two Stage Vmd and Atrial Fibrillation Diagnosis Index," *J. Mech. Med. Biol.*, vol. 17, no. 7, pp. 1–20, 2017.

[8] P. Schwab, G. C. Scebba, J. Zhang, M. Delai, and W. Karlen, "Beat by Beat : Classifying Cardiac Arrhythmias with Recurrent Neural Networks," vol. 44, pp. 1–4, 2017.

[9] B. S. Chandra, C. S. Sastry, S. Jana, and S. Patidar, "Atrial Fibrillation Detection Using Convolutional Neural Networks," vol. 44, pp. 1–4, 2017.

[10] S. Kiranyaz, T. Ince, O. Abdeljaber, O. Avci, and M. Gabbouj, "1-D Convolutional Neural Networks for Signal Processing Applications," pp. 8360–8364, 2019.

[11] V. Sze, S. Member, Y. Chen, S. Member, and T. Yang, "Efficient Processing of Deep Neural Networks : A Tutorial and Survey," pp. 1–32.

[12] G. D. Clifford *et al.*, "AF Classification from a Short Single Lead ECG Recording : the PhysioNet / Computing in Cardiology Challenge 2017," vol. 44, pp. 1–4, 2017.

[13] F. Liu *et al.*, "An Open Access Database for Evaluating the Algorithms of Electrocardiogram Rhythm and Morphology Abnormality Detection," *J. Med. Imaging Heal. Informatics*, vol. 8, no. 7, pp. 1368–1373, Sep. 2018.

[14] J. Zheng, J. Zhang, S. Danioko, H. Yao, H. Guo, and C. Rakovski, "A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients," *Sci. Data*, vol. 7, no. 1, p. 48, Dec. 2020.