Best Parameters Selection of Arrhythmia Classification Using Convolutional Neural Networks

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***Abstract*—Arrhythmia are disturbances in the heart where the heart beats slower or faster. Some types of Arrhythmia can became a serious problem and life-threatening. Early detection of Arrhythmia is very crucial to patients. Tools that can be used to determine heart condition is Electrocardiogram (ECG). Deep learning methods can be used to classify types of Arrhythmia from ECG images. Convolutional Neural Network is one of deep learning methods that is often used to classify images. CNN-based model such as VGG, ResNet, and MobileNet has gotten success in images classification. Those models are using lots of convolution layer, so those models are easily run into over fitting problem if those are used in small dataset. CNN model in this research needs parameter adjustments to solve over fitting problem. Parameter that were being adjusted were learning rate, dropout rate, and the number of convolution layer. The testing results on CNN model showed that the best learning rate and dropout rate which produced the best model to classify Arrhythmia were 0.0001, and 0.0075 respectively. The number of convolution layers which obtained the best accuracy was 4. Classification using CNN model for Arrhythmia with learning rate, dropout rate, and number of convolution layers were 0.0001, 0.0075, and 4 respectively resulted in the best model with 94.2% accuracy value.**

***Keywords*— arrhythmia, electrocardiogram, deep learning, convolutional neural network**

I. Introduction

Cardiovascular disease becomes one of deadliest disease in the world [1]. One type of this disease is Arrhythmia. Arrhythmia are disturbances in the heart where the heart beats slower or faster [2]. Some types of Arrhythmia can became a serious problem and life-threatening, such as the failure of blood pumping by heart. This failure can cause problems in brain, lung and others which lead to stroke or sudden cardiac death. For example, one of the most common type of arrhythmia, Premature Ventricular Contraction (PVC), contributes more than 50% of deaths among various Cardiovascular disease [3].

One of the tools that can be used to diagnose heart condition of patients is Electrocardiogram (ECG). ECG is used to record heart activity in signal form [4]. ECG is the noninvasive tools to detect various Arrhythmia, early detection of Arrhythmia is very crucial to patients as they can cause sudden cardiac death. Automatic diagnosis using computer assisted methods have been developed to help diagnosing Arrhythmia because their unknown mechanisms, complex nature, and clinical interrelations [5]. One of them is classification of ECG using machine learning.

Machine learning can be used for classification process either using ECG signals or ECG images converted from them. Many works in this have been done using many different machine learning technique. Sannino et. al [6] have used Deep Neural Networks to classify Arrhythmia using features extracted from ECG signals. The proposed model can classify ECG on whole dataset with 99.8% accuracy. Another study using Deep Beliefs Networks also shows that ECG signals can be used for classification[7].

Another technique that can be used for classification process is Convolutional Neural Networks (CNN). CNN is one of deep learning methods that has been used by many in images classification. CNN is used due to the fact that it is hard to identify ECG components [5]. Many studies have been done to classify Arrhythmia using CNN on ECG. Kiranyaz et. al [8] has been using feature extracted from ECG signals in 1-dimension CNN. Acharya et. al [9] have been conducted study using ECG signal to classify Tachycardia with CNN. Jun et. al [10] has also been using CNN in ECG classification using ECG images. Their model outperforms Kiranyaz et. al [8] with accuracy reaches 99%.

The problems that usually surfaced in using CNN is long training time. This is caused by a lot of trainable parameters which are processed through training process. The architecture of CNN affects these parameters. To make the training process faster, it requires a decent hardware. As example Jun et. al [10] uses 2 server grade hardware to train their model. And this hardware is not easily accessible by college student or small budget researchers.

Another thing that affects training time is data. More data used in training means longer training time. Jun et. al [10], Kiranyaz et. al [8] use entire dataset in open-source dataset for their study.

Another problem caused by CNN architecture is over fitting. Dropout regularization can be used to decrease over fitting [11]. Srivasta et. al [11] shows that using dropout in CNN can increase its performance.

Based on the problems, we conduct experiment to select the best parameters for CNN model to classify Arrhythmia based on ECG images with small dataset rather than whole dataset which usually takes up larger number, without sacrificing model performance. The parameters include learning rate, dropout rate, and number of convolution layers.

Our methods in this paper consists the following steps: data acquisition, data preprocessing, data partition, and parameter selection. ECG signals data used in this paper is obtained from MIT-BIH dataset [12]. With these data, we obtain ECG images from transformed ECG signals. In this paper we use small dataset number as opposed to usual works which used whole data in dataset. We use a portion of ECG

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images obtained. The parameter selection is done with grid search method resulting in several CNN model.

The rest of this paper is organized as follows. Section 2 describes related works in Arrhythmia classification, Section 3 describes methodology used for Arrhythmia Classification. Experiments Setup and their results are described in Section 4. Section 5 draws conclusion of the paper.

II. Related Works

Many methods had been used to classify Arrhythmia such as using feature extraction from signal or use ECG images.

In [13] and [14], the authors used Karhunen-Loeve transform (KLT) representation of ECG signal and used Expectation Maximization (EM) algorithm to reduce the numbers of parameters in Gausian Mixture Model. The classification was done by using SVM classifier. In [15], the authors combines principal component analysis (PCA) and modified fuzzy one-against-one (MFOAO) and uses Fuzy SVM in binary classification of ECG.

Others were using deep learning rather than classical machine learning classifier. In [6], the study were using Deep Neural Network in extracted features of ECG signals. Mathews, et. al [7] used Deep Beliefs Network to classify beats.

ECG Images could also be used for classification such as in [10] which used 2D images representation of ECG signal. Wu, et. al [16] compares 1D and 2D representation of ECG using CNN and showed that 2D representation outperforms 1D representation in terms of accuracy. The authors used CNN classifier on large numbers of ECG images.

III. Methods

The process in this paper consist of following steps : Data acquisition, Data Preprocessing, Data Partition , Parameter Selections, and Training model. Overall steps are shown in Fig 1.

A. Convolutional Neural Networks

Convolutional Neural Networks (CNN) is artificial neural network architecture specialize in processing grid-topology data [17]. Further, the CNN can self-learn and self-organize which does not require supervision. CNN has also been applied in diverse applications such as object recognition, image classification, and handwriting classification. It is also used in the medical field as an automated diagnostic tool to aid clinicians [9]

B. Data acquisition

Dataset used in this paper is obtained from MIT-BIH dataset [12]. Each data in dataset is presented in 3 files, annotation file, header file, and data signal file itself. There are 48 ECG signal records with 2 channels in this dataset. In this paper, we do not follow AAMI recommendation in class labelling and result presentation. Some types of arrhythmia found in this dataset are Ventricular Escape Beat (VEB), Atrial Premature Cotraction (APC), Normal Beat, Left Bundle Branch Block (LBB), Paced Beat, Fusion of Paced and Normal Beat, Premature Ventricular Contraction (PVC), Right Bundle Branch Block (RBB), and Unclassified beat.

We use 6 of those types as we found that those types had sufficiently high number of data to build dataset in this study. The 6 classes are Atrial Premature Contraction (APC), Normal Beat, Left Bundle Branch Block (LBB), Paced Beat, Premature Ventricular Contraction (PVC), and Right Bundle Branch Block (RBB).

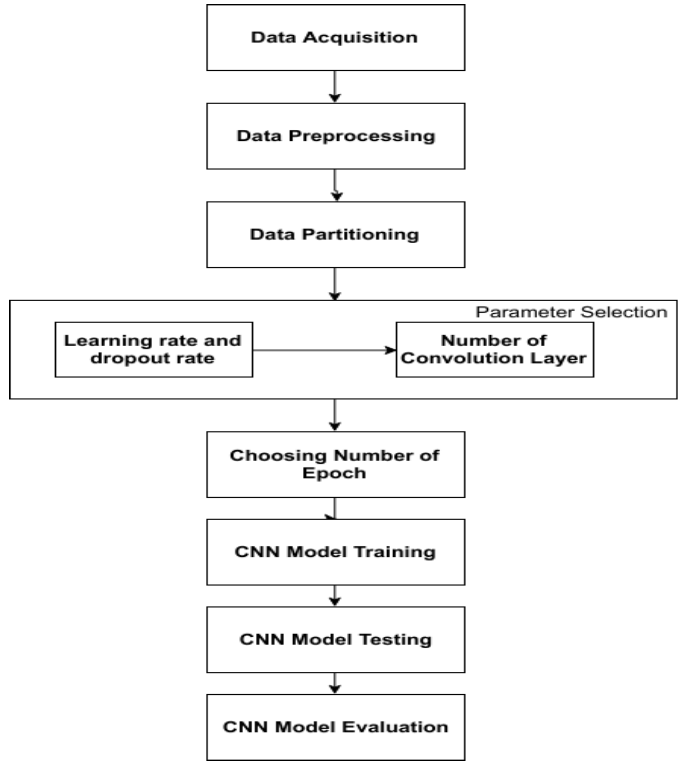

Fig. 1. Overall methods in this study

C. Data Preprocessing

Each ECG signal will be transformed to ECG image. The overall processes are shown in Fig 2. To transform signals, first, we read the signals from files and divide it to 6 class that will be used. Each series of signals then will be segmented to beats. To segment a beat, we detect R peaks using R peak detection (Christov Segmenter) [18], once the R peaks have been found, we define a single beat as the signals between half of the distance between current R peak and last R peak. For every segmented beat, we transform it to 128x128 gray scale image using matplotlib library. Fig 3 shows examples of segmented beat of ECG images.

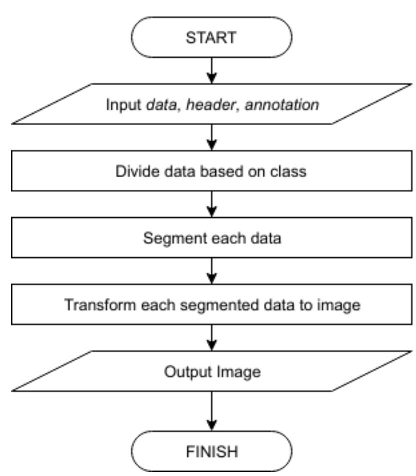

Fig. 2. Flowchart data preprocessing

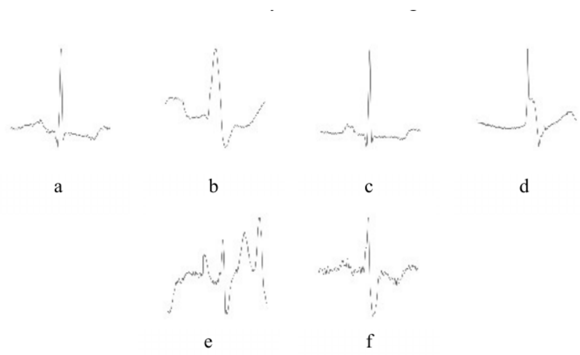

Fig. 3. Examples of ECG images. (a) APC, (b) LBB
(c) Normal, (d) Paced Beat (PAB), (e) PVC, (f) RBB

TABLE I DATA PARTITION OF DATASET

N	Class	Training Data	Validation Data	Testing Data	Total Data
1	APC	1474	377	448	2299
2	LBB	2945	734	967	4646
3	Normal	2985	733	892	4610
4	PAB	3023	726	963	4712
5	PVC	3023	791	897	4711
6	RBB	2934	735	953	5622

D. Data Partition

We build our dataset in 3 set of data, Training, Validation, and Testing. This method does not follow AAMI recommendation. To build our dataset, we choose randomly 25600 images from 6 classes of data with near balanced method. Those images are then divided into training set and testing dataset. Training and testing dataset are 80% and 20% of those images respectively. Training dataset is then divided again to create validation dataset which is 20% of training dataset. Table 1 shows data partition of training, validation, and testing.

E. Parameter Selection

3 parameters will be tested to select the best value. Those parameters are learning rate, dropout rate, and number of convolutional layer. Each parameter will be tested with different value and the value that resulted in the best performance model will be selected.

F. CNN Model Training and Testing

Model will be trained and tested with pre-configured parameter. Each model will be training using same dataset. All model use ELU activation function in between layer and Softmax activation function in output layer. Loss function used in all model is Categorical Cross Entropy.

G. CNN Model Evaluation

All model will be evaluated based on their accuracy, precision and sensitivity on testing dataset. The best model with best performance will be selected its parameters.

H. Evaluation Metrics

In this paper, we use accuracy, sensitivity, and precision to evaluate the model and choose best parameters for model. Specificity is the fraction of negative test results that are correctly identified as normal. Sensitivity is the probability of positive test results that are correctly identified as arrhythmia. The metrics are defined in the following equation

$$Accuracy(\%) = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Sensitivity(\%) = \frac{TP}{FP+FN} \tag{2}$$

$$Precision(\%) = \frac{TP}{TP+FP} \tag{3}$$

– True Positive (TP) : Correctly detected as arrhythmia
– True Negative (TN) : Correctly detected as normal
– False Positive (FP) : Incorrectly detected as arrhythmia
– False Negative (FN) : Incorrectly detected as normal

I. Experiment Scenarios

The experiment consists of 3 scenario. These scenarios are based on parameter selection. The following describes all 3 scenarios :

1) Scenario 1: This scenario is firstly done to set epoch number which will be used for next experiment. The number of epoch being tested are 15 to 40 with 5 range. The model that will be used for this scenario is shown in Table 2.

2) Scenario 2: This scenario is done to determine the best learning rate and dropout rate. The value of learning rate that were tested are 0.01, 0.001, and 0.0001. While dropout rate that were tested are 0.05, 0.1, and 0.01.

3) Scenario 3: This scenario is done to determine the number of convolutional layers used in CNN model. The number which were being tested are 4, 6 and 8 convolutional layers. Table III, IV, and V shows the 3 model tested in this scenario.

TABLE II 4 CONVOLUTION LAYER MODEL

Layer	Layer Type
Layer 1	Conv2D
Layer 2	Conv2D
Layer 3	Pooling
Layer 4	Conv2D
Layer 5	Conv2D
Layer 6	Pooling
Layer 7	Fully Connected
Layer 8	Output

TABLE III 4 CONVOLUTION LAYER MODEL

Layer	Layer Type
Layer 1	Conv2D
Layer 2	Conv2D
Layer 3	Pooling
Layer 4	Conv2D
Layer 5	Conv2D
Layer 6	Pooling
Layer 7	Fully Connected
Layer 8	Dropout
Layer 8	Output

TABLE IV 6 CONVOLUTION LAYER MODEL

Layer	Layer Type
Layer 1	Conv2D
Layer 2	Conv2D
Layer 3	Pooling
Layer 4	Conv2D
Layer 5	Conv2D
Layer 6	Pooling
Layer 7	Conv2D
Layer 8	Conv2D
Layer 9	Pooling
Layer 10	Fully Connected
Layer 11	Dropout
Layer 12	Output

TABLE V 8 CONVOLUTION LAYER MODEL

Layer	Layer Type
Layer 1	Conv2D
Layer 2	Conv2D
Layer 3	Pooling
Layer 4	Conv2D
Layer 5	Conv2D
Layer 6	Pooling
Layer 7	Conv2D
Layer 8	Conv2D
Layer 9	Pooling
Layer 10	Conv2D
Layer 11	Conv2D
Layer 12	Pooling
Layer 13	Fully Connected
Layer 14	Dropout
Layer 15	Output

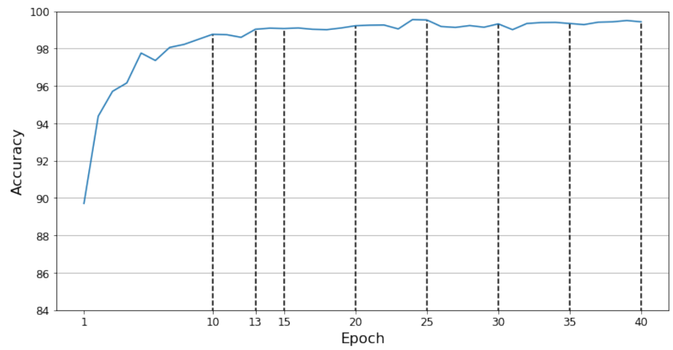

Fig. 4. Scenario 1 results

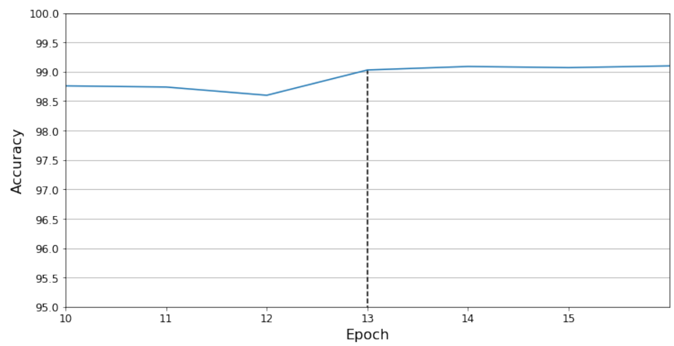

Fig. 5. Scenario 1 results in 10-15 epochs

IV. Results and Discussion

A. Scenario 1

Epoch used in this scenario are 10, 15, 20, 25, 30, 35, and 40. Learning rate was 0.001. Fig 4 showed the accuracy for every epoch in each model tested in this scenario. Trained models reached stable accuracy value when the epoch hit 10 epoch as shown in Fig 4. Models that have been trained with epoch more that 10, resulted accuracy that changes only a little over times. This happened when epoch started hitting 13 as shown Fig 5. After that, models kept getting constant accuracy within range 98%-99.5%. Based on this result, we use 13 epoch for next experiment. The model in this scenario then tested with 13 epocch and the result showed that this model is having overfitting problem in Arrhythmia classification. This model only reached testing accuracy as high as 54%. This overfitting problem can be solved using dropout layer and tuning the number of convolutional layer.

B. Scenario 2

This scenario was done with adding dropout layer in model used in scenario 1. Inital values of dropout rate that were tested in this scenario were 0.01, 0.1, 0.5. Learning rate was also being tuned with initial values 0.01, 0.001, and 0.0001. These two parameters were being tested using grid search resulted in 9 models. The results of this scenario is shown in Table VI and Fig 6.

TABLE VI LEARNING RATE AND DROPOUT RESULTS

No	Dropout Rate	Learning Rate	Accuracy (%)
1	0.01	0.01	59.5
2	0.01	0.001	60.4
3	0.01	0.0001	90.4
4	0.1	0.01	56.9
5	0.1	0.001	39.5
6	0.1	0.0001	70.8
7	0.5	0.01	44.6
8	0.5	0.001	34.9
9	0.5	0.0001	32.4

Learning rate 0.0001 made better performance model that learning rat 0.01 and 0.001. So this value was selected to be used in the next experiment. As for dropout rate, smaller dropout rate gave better models as shown in Fig 6. Dropout rate 0.01 gave the best accuracy out of 3 values. The effects on adding dropout layers were shown in Fig 7 and 8. Those images showed taht without dropout there were still noises in images. This caused the shape of beat was still hard to be distinguished. Next experiment in this scenario was conducted using new dropout rates, smaller than 0.01. The new dropout rates were 0.0075, 0.005, 0.0025, and 0.001. Learning rate 0.0001 was used for this experiment. The results showed that dropout rate 0.0075 could make the model classify better with accuracy 92%.

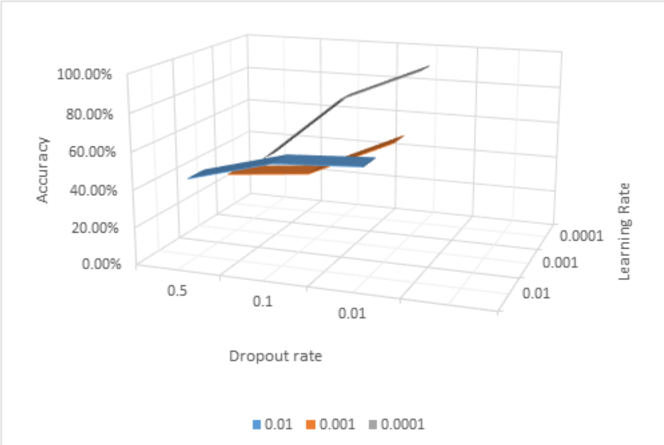

Fig. 6. Scenario 2 results

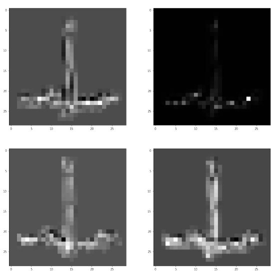

Fig. 7. Normal Beat

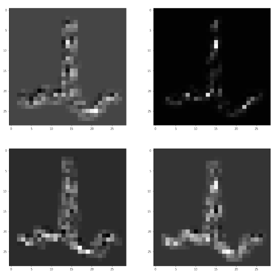

Fig. 8. PVC

TABLE VII SCENARIO 3 RESULTS

Number of Convolution Layer	Accuracy	Precision	Sensitivity
4	94.2	94.7	93.9
6	92.4	92.7	91.1
8	88.1	88.8	87.6

C. Scenario 3

This scenario tested some models with different number of convolutional layer. The number of convolutionallayer tested were 4, 6, and 8 layer. The selected parameters from scenario 2, learning rate 0.0001 and dropout rate 0.0075, were used in this scenario. These model were trained in 13 epoch. Table VII and Fig 9 showed the result for these model in this scenario. Based on those result, the model that could classify Arrhythmia better was model with the smallest number of layers, 4 layers. This result mean that more convolution layer did not mean better performace. The performance of models kept decreasing as the number getting higher. This decreasing performance was caused by feature map in model with high number of convolution layers had became too specific.

The effects of convolution layer in feature map are shown in Fig 10-15. Those images showed 4 feature map from each models. These feature maps are sample of many feature maps. In those images the bright area or called activation area showed that those area were detected by model's filter as a feature of heart beat. In model with 4 layer, activation area were still shaped like a heartbeat itself. Otherwise, in model with 8 layers, filter had been analyzing the edge of heartbeat. As the number of convolution layer kept getting higher the feature map became more specific.

More convolution layers in CNN model resulted in decreasing accuracy in Arrhythmia classification because the shape of heart beat was fading away. This faded away data made the model could not easily distinguish one class with another.

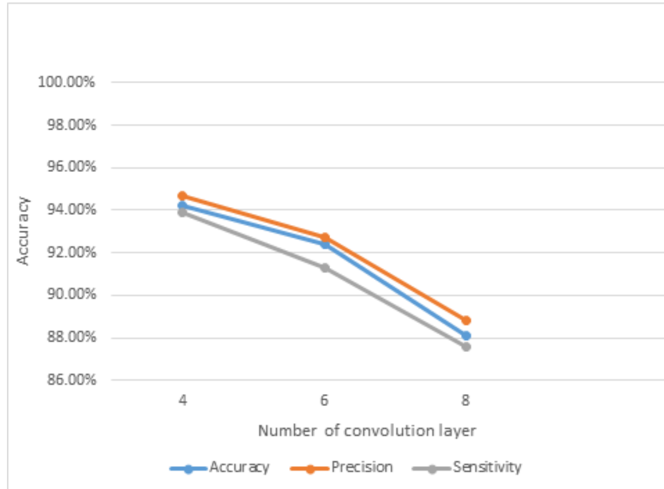

Fig. 9. Scenario 3

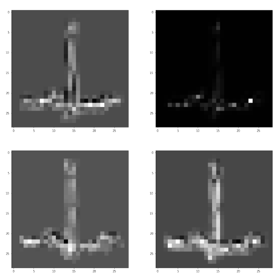

Fig. 10. Normal Beat

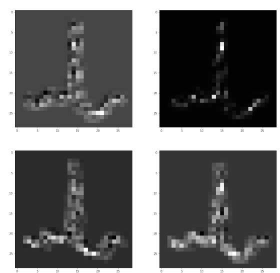

Fig. 11. PVC

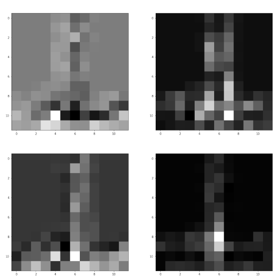

Fig. 12. Normal Beat

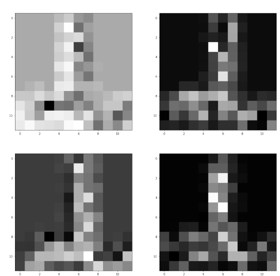

Fig. 13. PVC

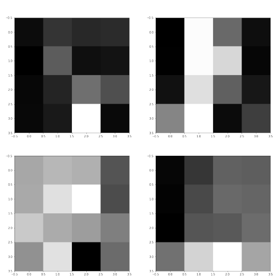

Fig. 14. Normal Beat

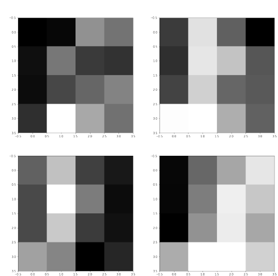

Fig. 15. PVC

V. Conclusion

Based on the results the study, the optimum number of epoch to train model is 13. Using dropout layer and tuning learning rate can help solving over fitting problem as shown in accuracy getting better and reached 90%. The best dropout rate and learning rate are 0.0075 and 0.0001 respectively. And optimum number of convolutional layer is 4. With these parameters CNN model can classify Arrhythmia with the best performance. Its accuracy, precision and sensitivity are 94.2%, 93.9%, and 94.7%.

References

[1] WHO. Cardiovascular diseases (CVDs).

[2] Brian Olshansky. *Arrhythmias*. Elsevier Inc., fourth edi edition, 2018.

[3] Hussain AL-Ziarjawey. Heart Rate Monitoring and PQRST Detection Based on Graphical User Interface with Matlab. *International Journal of Information and Electronics Engineering*, 5(4):311–316, 2015.

[4] American Heart Association. Electrocardiogram (ECG or EKG) — American Heart Association.

[5] Roshan Joy Martis, U. Rajendra Acharya, and Hojjat Adeli. Current methods in electrocardiogram characterization. *Computers in Biology and Medicine*, 48:133 – 149, 2014.

[6] G. Sannino and G. De Pietro. A deep learning approach for ECG-based heartbeat classification for arrhythmia detection. *Future Generation Computer Systems*, 86:446–455, 2018.

[7] Sherin M. Mathews, Chandra Kambhamettu, and Kenneth E. Barner. A novel application of deep learning for single-lead ECG classification. *Computers in Biology and Medicine*, 99(May 2017):53–62, 2018.

[8] Serkan Kiranyaz, Turker Ince, and Moncef Gabbouj. Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks. *IEEE Transactions on Biomedical Engineering*, 63(3):664–675, 2016.

[9] U. Rajendra Acharya, Hamido Fujita, Oh Shu Lih, Yuki Hagiwara, Jen Hong Tan, and Muhammad Adam. Automated detection of arrhythmias using different intervals of tachycardia ecg segments with convolutional neural network. *Information Sciences*, 405:81 – 90, 2017.

[10] Tae Joon Jun, Hoang Minh Nguyen, Daeyoun Kang, Dohyeun Kim, Daeyoung Kim, and Young-Hak Kim. ECG arrhythmia classification using a 2-D convolutional neural network. 2018.

[11] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research*, 15:1929–1958, 2014.

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

[13] Giorgio Biagetti, Paolo Crippa, Alessandro Curzi, Simone Orcioni, and Claudio Turchetti. A Multi-class ECG beat classifier based on the truncated KLT representation. *Proceedings - UKSim-AMSS 8th European Modelling Symposium on Computer Modelling and Simulation, EMS 2014*, (2):93–98, 2014.

[14] Paolo Crippa, Alessandro Curzi, Laura Falaschetti, and Claudio Turchetti. Multi-class ECG beat classification based on a gaussian mixture model of karhunen-loève transform. *International Journal of Simulation: Systems, Science and Technology*, 16(1):2.1–2.10, 2015.

[15] Mohamed Cherif Nait-Hamoud and Abdelouaheb Moussaoui. Two novel methods for multiclass ECG arrhythmias classification based on PCA, fuzzy support vector machine and unbalanced clustering. *2010 International Conference on Machine and Web Intelligence, ICMWI 2010 - Proceedings*, pages 140–145, 2010.

[16] Yunan Wu, Feng Yang, Ying Liu, Xuefan Zha, and Shaofeng Yuan. A Comparison of 1-D and 2-D Deep Convolutional Neural Networks in ECG Classification. *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, 2018:324–327, 2018.

[17] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016.

[18] Ivaylo I. Christov. Real time electrocardiogram QRS detection using combined adaptive threshold. *BioMedical Engineering Online*, 3:1–9, 2004.