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Enhancing the performance of heart arrhythmia prediction model using Convolutional Neural Network based architectures

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ABSTRACT

Heart disease is one of the diseases that exposes high mortality worldwide. This conventional way of predicting heart disease is usually expensive, time-consuming, and prone to human error. Early detection of heart disease is important as it helps to prevent deaths caused by this disease. Machine learning utilization as the non-invasive means for predicting heart disease is considered as a fast and affordable method to prevent the fatality of heart disease. This work aims at utilizing Convolutional neural network (CNN) to enhance the performance of an Arrhythmia prediction model. We have built an Arrythmia prediction model using neural networks comprising multiple convolutional layers and maxpooling layers. Our proposed model is trained using the MIT-BIH Arrhythmia dataset. The model performance has been evaluated and the model achieves 98.43% of performance accuracy.

1. Introduction

Heart disease is a health condition that disrupts the performance of the heart and blood vessels. Heart disease includes a number of conditions, namely coronary artery disease (CAD), heart arrhythmias, heart valve disease, cardiomyopathy (heart muscle disease), and congenital heart disease. Heart disease is one of the diseases that exposes high mortality worldwide [1]. Based on the World Health Organization (WHO) data, around 17.9 million deaths are caused by heart disease per year [2]. The American Heart Association stated 121.5 million Americans suffered from heart disease in 2016 [3]. In Indonesia itself, heart disease causes 14.38% of deaths in Indonesia [4]. The detection of heart disease is usually conducted by examining several factors, such as blood pressure, blood sugar level, and also cholesterol level. Moreover, ECG signal is also used to detect irregularities of heart beats which may indicate a heart disease. This conventional way of predicting heart disease is usually expensive, time-consuming, and prone to human error [5]. Early detection of heart disease is important as it helps to prevent deaths caused by this disease [6], [7].

In this Artificial Intelligence (AI) era, various AI based disease prediction models have been developed by biomedical researchers. The advancement of AI based disease prediction models are driven by two main factors: the availability of abundant patient data which provide valuable insights and the machine learning techniques to recognize patterns from the data. With respect to heart disease prediction, various machine learning based models have been developed. Machine learning utilization as the non-invasive means for predicting heart disease is considered as a fast and affordable method to prevent the fatality of heart disease. Hungary, Cleveland, Long Beach, Switzerland, and Framingham datasets are most commonly used datasets to predict CAD [8]. They are used widely by biomedical researchers to build CAD predictive models [9]–[13]. Almustafa [9] built a CAD predictive model using Decision Tree, K-Nearest neighbour, and JRip with a performance accuracy of 99.70%. Gárate-Escamila et al [10] implemented PCA for feature extraction and built a CAD predictive model using Random forest classifier. It achieved a performance accuracy of 99%. Ghosh et al [11] utilized Relief and Least Absolute Shrinkage and Selection Operator (LASSO) feature selection methods and trained a CAD predictive model using various ensemble methods including Decision Tree, Random Forest, K-Nearest Neighbors, AdaBoost, and Gradient Boosting. The model successfully achieved 99.05% of prediction accuracy. Fitriyani et al [12] used DBSCAN to eliminate anomalies from the dataset, SMOTE-ENN to balance the training data distribution, and XGBoost to classify the CAD. It achieved 98.40% performance accuracy.

Besides the aforementioned CAD prediction studies, previous researchers also utilized neural networks to build CAD prediction models. Convolutional Neural Networks (CNN) has been widely used to build neural networks based CAD prediction models. Shen et al [13] implemented 3D Fully Convolutional Network and gained 90.05% performance accuracy. Acharya et al [14] implemented 11-layer deep CNN and achieved 95.22% performance accuracy. Sofian et al [15] utilized 34 layers of residual networks, ResNet101, and gained 99.49% accuracy. Tan et al [16] utilized 8 layers of deep CNN and gained 99.85% of performance accuracy in CAD prediction. Previous studies have shown that convolutional network based architectures have a stable performance in CAD prediction with the accuracy gained is beyond 90%.

Apart from CAD prediction, machine learning and neural networks methods have been utilized for Arrhythmia detection. Arrhythmia is defined as a condition in which the heart beats with irregular or abnormal rhythm. The most popular dataset used in Arrhythmia detection is the MIT-BIH Arrhythmia dataset [17], [18]. This dataset has been used in [19]–[21]. Yıldırım at al [20] used one-dimensional CNN to predict Arrhythmia on long duration ECG based on the MIT-BIH Arrhythmia dataset and achieved 91.33% of accuracy. Chen et al [20] developed Arrhythmia prediction model by using a combination of CNN and Long Short Term Memory (LSTM) and showed 99% performance accuracy. Hammad et al [21] utilized a combination of CNN and Convolutional LSTM in the Arrhythmia prediction model architecture and achieved 98% of accuracy. Although the accuracy gained by previous models in predicting Arrhythmia is remarkably good, those models tend to have complex architectures that result in a huge number of parameters to train, which affects the computational resources needed to train the models.

This work aims at utilizing CNN to enhance the performance of an Arrhythmia prediction model. The experiments are conducted to see if the ability to recognize Arrhythmia patterns can be maximized by using convolutional layers and pooling layers only. We build a simple neural network architecture to minimize the number of trained parameters but to achieve a decent performance accuracy. Our proposed model comprises multiple convolution layers with various dimensions. Moreover, our paper is organized as follows: introduction, the algorithm, proposed method, results and discussion, and conclusion.

2. The Proposed Method/Algorithm

2.1. Convolutional Neural Networks

Deep learning (DL) has emerged as a state-of-the-art algorithm in artificial intelligence, driven by the availability of large datasets [22]–[25]. DL consists of multiple sequential layers where inputs are passed to the next layer in a feed-forward manner. Higher-level layers learn more abstract representations of the input data to perform specific tasks and generate outputs [26]–[28]. Deep learning models consist of hidden layers that learn and correct errors through the backpropagation algorithm [29]. Unlike traditional machine learning algorithms, which often require extensive feature extraction and selection that makes them slower and more computationally expensive, deep learning models automatically extract useful features from data [30], [31]. A study [32] even demonstrated that a deep learning model outperformed cardiologists in predicting arrhythmias from ECG signals. In many medical fields, deep learning has demonstrated an outstanding performance in improving prediction accuracy and reducing costs [30], [32], [33]. This success is largely attributed to its ability to learn complex features directly from raw data, eliminating the need for extensive preprocessing and feature engineering [23], [25], [34].

Despite its advantages, deep learning faces several challenges that hinders the implementation of this algorithm, such as increased training time due to the multiple layers in its architecture [31] and a large number of parameters used, which can lead to overfitting and higher computational complexity [24]. Additionally, in domains like ECG classification, training data is often limited, making it difficult to achieve optimal performance [23], [32]. Parameter optimization is also a crucial but time-consuming process, as selecting the most suitable hyperparameters significantly impacts model performance [35].

Convolutional Neural Networks (CNN) are among the most commonly used deep learning models [25], [26], [30]. CNNs work similarly to the human visual system, making them particularly effective for computer vision tasks such as image classification and object detection [36]–[41]. They are especially powerful in feature extraction and classification [22]. However, CNNs performance heavily depends on the size of the training dataset [29].

In ECG classification tasks, CNNs play a crucial role in identifying the best feature representations from input data and analyzing those features for accurate categorization [42]. A typical CNN architecture consists of convolutional layers, pooling layers, normalization layers, and fully connected layers, each serving a specific role in transforming input data into meaningful representations [35], as shown in Fig. 1. The fully connected layer is responsible for classification, while other layers are in charge of feature extraction [26]. Through convoluting and subsampling, CNNs extract essential features from input data using kernels or filters, which generate feature maps [22], [25], [43]. The overall CNN architecture can be adjusted by modifying parameters such as the number of convolutional layers, kernel size, stride, the number of neurons in fully connected layers, and learning rate [22], [44].

Although CNNs were originally designed for two-dimensional data, they have been successfully adapted for one-dimensional data sequences. 1D CNNs are particularly effective in integrating both feature extraction and classification into a single learning body, eliminating the need for domain expertise, making them suitable for real-time monitoring as it is more compact and faster [37], [45]. The primary difference between 1D and 2D CNNs lies in the dimensionality of the arrays used for kernel weights, inputs, and outputs.

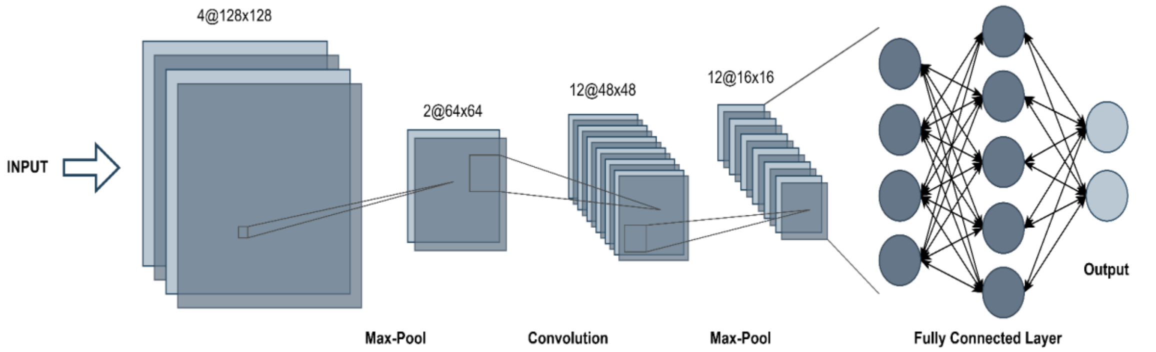

Fig. 1. Illustration of CNN Architecture [36]

2.2. Performance Metrics

A confusion matrix is widely used to evaluate the performance of classification models [45]. This metric summarizes the number of instances in the test sets that are correctly and incorrectly classified. A true positive (TP) occurs when the model correctly identifies a positive instance as positive, while a false positive (FP) occurs when the model incorrectly classifies negative instance as positive. On the other hand, a true negative (TN) represents the number of negative instances correctly identified as a negative class, whereas a false negative (FN) occurs when the model incorrectly classifies a positive instance as negative.

These metrics are used to calculate various performance criteria, such as accuracy (ACC), precision (PRE), Recall or sensitivity (SEN), and F1 score [46], [47]. Precision measures the proportion of correctly identified positive instances out of all positive instances predicted by the model. A high precision value indicates the model rarely misclassified negative instances as positive [45]. In medical applications, high precision signifies the model's ability to correctly detect disease while minimizing false alarms [46]. Recall or sensitivity measures the proportion of correctly classified positive instances relative to all true positive instances. F1 score combines both precision and recall into a single value, providing a balanced evaluation on the model's performance. Additionally, accuracy represents the ratio of correctly classified positive and negative instances to total number of observations in the test sets. However, accuracy needs to be interpreted with caution, as it is influenced by class imbalance in the dataset [46].

The mathematical formulations of those evaluation criteria are defined as follows [46], [47]:

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

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ Score = \frac{2*(Recall*Precision)}{Recall+Precision} \tag{4}$$

3. Method

In this section, the dataset, the neural network architectures, and the hyperparameter setting used in the experiments are described.

3.1. Dataset

In this work, the MIT-BIH Arrhythmia dataset is used to train the arrhythmia prediction model. This dataset is taken from the Physionet repository [16]. The dataset originated from The MIT-BIH Arrhythmia database which contains 48 half-hour excerpts of two-channel ambulatory ECG recordings. It was obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were arbitrarily chosen from a set of 4000 24-hour ambulatory ECG recordings. The recordings were collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital. The MIT-BIH Arrhythmia dataset was initially used in [18].

The MIT-BIH Arrhythmia dataset contains 100,689 data with 32 features. The target class for the dataset consists of five classes including 'F' (Fusion Beats), 'N' (Normal), 'Q' (Unknown Beats), 'SVEB' (Supraventricular ectopic beats), 'VEB' (Ventricular ectopic beats). The dataset is actually imbalanced. The distribution of instances in the dataset is shown in Fig. 2.

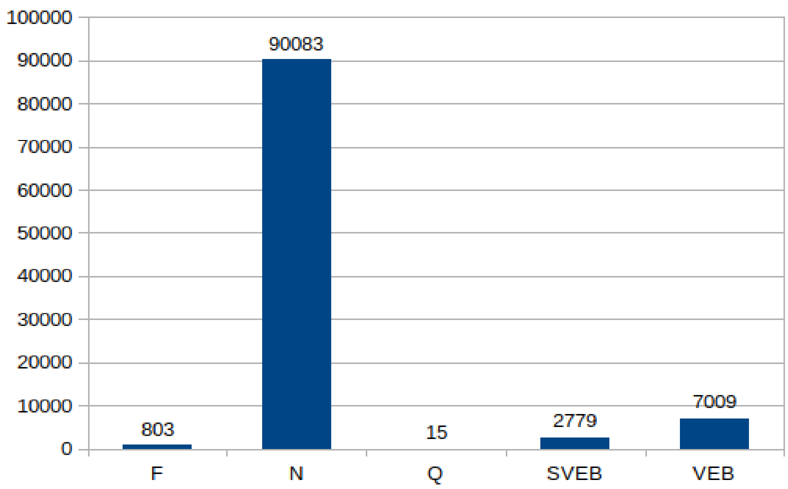

Fig. 2. Data Distribution in The MIT-BIH Arrhythmia Dataset

We split the dataset randomly into training dataset and test dataset with the proportion of 70:30. Moreover, we split the training dataset for training and validation with the proportion of 90:10

3.2. Network Architecture

In this work, we propose a neural network based arrhythmia prediction model. We propose a neural network architecture comprising multiple convolutional layers to extract the valuable information from the MIT-BIH dataset. The details of the network is shown in Fig. 3. The network receives an input of length 32 (as it has 32 features). The network then passes the input into multiple convolutional layers in which each layer includes a 1D convolution layer and a 1D maxpooling layer. The multiple convolutional layers are then followed by a flatten layer, to transform the resulting feature maps into a one-dimensional data. The last layer in the network architecture is the dense layer which produces the final result of the arrhythmia classification. During the experiment, the configuration of the convolutional layers is tested out. Several configurations are tried and the one leading to the best classification performance is selected to build the final model.

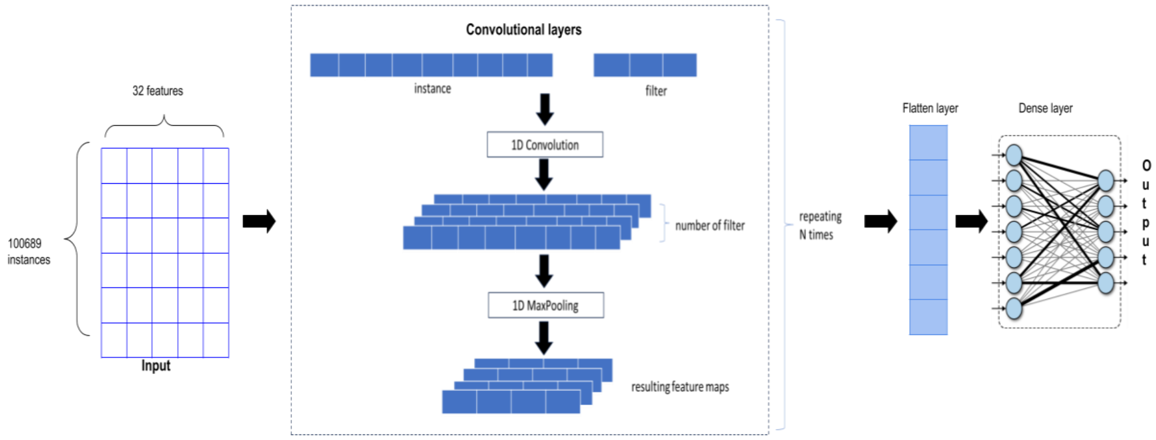

Fig. 3. The proposed neural network architecture

3.3. Hyperparameters

Hyperparameter setting plays an important role in the neural network training to shape the quality of the resulting model. In this work, we utilize the hyperparameter settings as shown in Table 1.

Table 1. Hyperparameter settings in the proposed neural network model

No	Hyperparameter	Value
1	Optimizer	Adam
2	Callbacks	EarlyStopping with: patience : 20 variable to monitor: validation loss
3	Batch Size	32
4	Epoch	100

4. Results and Discussion

4.1. Experiment Results

We have built three different network architectures comprising multiple convolutional layers and maxpooling layers to recognize hidden patterns of the MIT BIH Arrhythmia dataset (Fig. 4 depicts the details of each architecture). The first architecture, called Conv753-64, consists of a 1D-convolutional layer with filter/kernel size of 7, a 1D-convolutional layer with filter/kernel size of 5, a 1D-convolutional layer with filter/kernel size of 3, a 1D-maxpooling layer following each convolutional layer, a flatten layer, and a fully connected (dense) layer. The number of filters/kernels used in the first architecture is 64. The second architecture, called Conv753-128, has an identical network composition compared to the first one, except that it uses 128 filters/kernels. The third architecture, called Conv75-128, consists of only two 1D-convolutional layers with filter/kernel size of 7 and 5, a 1D-maxpooling layer following each convolutional layer, a flatten layer, and a fully connected (dense) layer. The third architecture also used 128 filters/kernels.

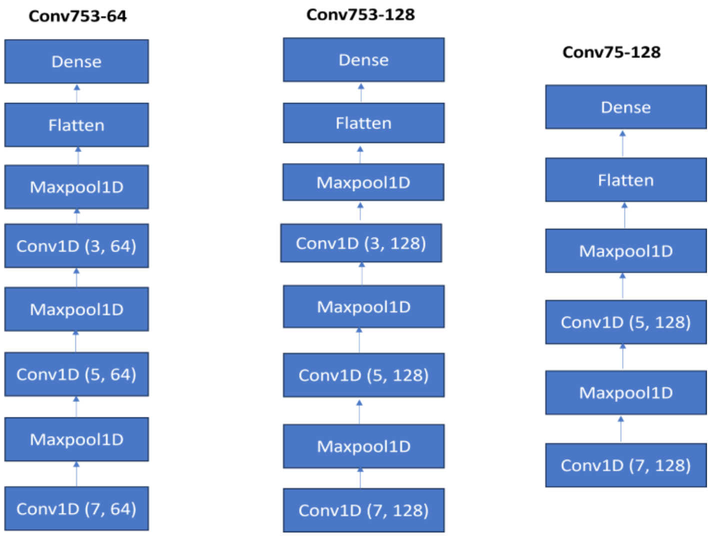

Fig. 4. Detailed Network Architectures

Table 2 shows the accuracy gained by each architecture.

Table 2. Performance Accuracy

Model	Accuracy (%)
Conv753-64	98.38
Conv753-128	98.43
Conv75-128	98.21

Besides the accuracy, we also examine the number of correctly predicted instances (True Positive) given by each model (shown in Table 3).

Table 3. The number of correctly predicted instances in each class

	Class	Correctly Predicted Instances
Conv753-64	F	165
	N	26896
	Q	0
	SVEB	688
	VEB	1970
Conv753-128	F	175
	N	26861
	Q	0
	SVEB	652
	VEB	1978
Conv75-128	F	195
	N	26879
	Q	0
	SVEB	708
	VEB	1950

The experiment results show that all models failed to predict a Q (unknown beats) instance. Conv75-128 can predict F (Fusion) and SVEB (Supraventricular ectopic beats) instances better than other models. Conv753-64 can predict N (normal beats) instances better than other models. Conv753-128 can predict VEB (Ventricular ectopic beats) instances better than other models.

Moreover, we also examine the precision, recall and F1-score achieved by each model. Table 4 shows the results. Conv753-64 predicts SVEB and VEB better than the other models as indicated in the precision, recall, and F1-Score achieved on those classes. All the models achieve identical precision, recall, and F1-score for N class.

Table 4. Classification metrics: Precision, Recall, and F1-Score by class

	Class	Precision	Recall	F1-Score
Conv753-64	F	0.88	0.68	0.77
	N	0.99	0.99	0.99
	Q	0	0	0.00
	SVEB	0.88	0.82	0.85
	VEB	0.96	0.95	0.95
Conv753-128	F	0.90	0.72	0.80
	N	0.99	0.99	0.99
	Q	0.00	0.00	0.00
	SVEB	0.87	0.78	0.82
	VEB	0.94	0.95	0.94
Conv75-128	F	0.86	0.80	0.83
	N	0.99	0.99	0.99
	Q	0.00	0.00	0.00
	SVEB	0.86	0.84	0.85
	VEB	0.96	0.94	0.95

The experiment results show that Conv753-128 architecture produces the highest overall performance accuracy compared to the other architectures. Hence, we select this architecture to build the final model. The output size of each layer in Conv753-128 architecture as well as the number of parameters in each layer is shown in Table 5. Conv753-128 architecture has 132,997 total parameters, including 132,997 trainable parameters and 0 non-trainable parameters.

Table 5. Output shape and number of parameters

Layer (type)	Output Shape	Param #
Conv1D	(Non, 26, 128)	1,024
MaxPooling1D	(None, 13, 128)	0
Conv1D	(None, 9, 128)	82,048
MaxPooling1D	(None, 4, 128)	0
Conv1D	(None, 2, 128)	49,280
MaxPooling1D	(None, 1, 128)	0
Flatten	(None, 128)	0
Dense	(None, 5)	645

4.2. Discussion

Based on the experiment results, there are two variables that contribute significantly to the performance of convolutional network based models. The first variable is the kernel/filter size. In this work, we use kernel/filter sizes of 7, 5, and 3. We use small kernel/filter size with the intention to analyze small patterns in the data. Eliminating the third convolutional layer (conv layer with kernel size of 3) from the model architecture (the Conv75-128 case) has reduced the overall performance of the model. The second variable affecting model performance is the number of kernels/filters used in each convolutional layer. Our experiment shows that when more filters are used in each convolutional layer (i.e 128 compared to 64), the overall performance of the model is also increased. The reason is clear because the more filters are used, the richer feature maps are generated and the model may learn more patterns from the data.

The experiments also show that all models have not successfully predicted a Q instance. In fact, the number of Q instances is very small (only 5 instances in the test set, 10 instances in the training set). The models failed to recognize the Q traits because the dataset does not have sufficient instances. In this work, we do not attempt to pre-process the dataset such that a more balanced dataset is generated, because we want to observe the capability of convolutional layers to recognize patterns directly from the imbalanced dataset. We found that although our models failed to recognize Q instances, our models are able to achieve a satisfying performance in predicting F and SVEB instances despite their limited number of instances. Thus, without balancing the dataset, the models are still able to learn patterns that differentiate each target class.

5. Conclusion

We have conducted experiments to observe three different neural network models utilizing convolutional layers to predict Arrhythmia. We use the MIT-BIH Arrhythmia dataset to build our models. Our final model architecture consists of a 1D-convolutional layer with filter/kernel size of 7, a 1D-convolutional layer with filter/kernel size of 5, a 1D-convolutional layer with filter/kernel size of 3, a 1D-maxpooling layer following each convolutional layer, a flatten layer, and a fully connected (dense) layer. Each convolutional layer uses 128 kernels/filters. Our model has been tested using 30% instances of the dataset and achieved 98.43% of accuracy. Besides accuracy, our model also shows a positive result by having a decent precision, recall, and F1-score for all classes, except Q, which is likely due to insufficient number of instances. Our model also has a relatively small number of parameters, which indicates that it does not require much computational resources.

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Declarations

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