Electrocardiogram Heartbeat Classification using Convolutional Neural Network-k Nearest Neighbor

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***Abstract*–Electrocardiogram (ECG) analysis is widely used by cardiologists and medical practitioners for monitoring cardiac health. A high-performance automatic ECG classification system is challenging because there is difficulty in detecting and categorizing different waveforms in the signal, especially in manual analysis of ECG signals, which means, a better classification system is needed in terms of performance and accuracy. Hence, in this paper, the authors propose an accurate ECG classification and monitoring system called convolutional neural network-k nearest neighbor (CNN-kNN). The proposed method utilizes 1D-CNN and kNN. Unlike the existing techniques, the examined technique does not need training during classifying the ECG signals. The CNN-kNN is evaluated against the PhysioNet's MIT-BIH and PTB diagnostics datasets. The CNN is fed using the ECG beat raw signal directly. In addition, the learned features are extracted from the 1D-CNN model and its dimensions are reduced using two fully connected layers and then fed to the k-NN classifier. The CNN-kNN model achieved average accuracies of 98% and 97.4% on arrhythmia and myocardial infarction classifications, respectively. These results are evidence of the great ability of the proposed model compared to the mentioned models in this article.**

***Index Terms*—Convolutional neural network, Electrocardiogram classification arrhythmia, K-nearest neighbor.**

I. Introduction

An electrical activity generated by the heart is called an electrocardiogram (ECG) signal. The ECG signal conveys information which is reflection the properties of the heart health condition. Therefore, diagnosis of the ECG signal is the main way to know the heart health condition. Consequently, analysis of the ECG signal became interesting to categorize the heart health condition. Due to certain limitations in disease classification based on the ECG including variance ECG morphology, Machine learning techniques have been widely applied to develop automatic heartbeat classification systems (Luz, et al., 2016). Machine learning techniques have been widely applied to develop automatic heartbeat classification systems (Luz, et al., 2016). Three different architectures of machine learning have been used for ECG diagnosis, namely traditional machine learning, deep machine learning, and hybrid machine learning architecture.

Effective feature extraction technique is the key success of traditional machine learning. In Saini, Singh, and Khosla (2013), a model developed based on the k nearest neighbor (kNN) classifier and some features that were adopted by applying a digital band-pass filter. Discrete wavelet transform (DWT) was addressed to an effective feature for the ECG signal and fed to the kNN algorithm (Bouaziz, Boutana and Oulhadj, 2019). The DWT was to train support vector machine (SVM). Venkatesan, et al. (2018) and Smíšek, et al. (2017) reported that a trained SVM through some morphological features could improve the accuracy rate for ECG classification. Mel Frequency Cepstrum Coefficient was used to feed artificial neuron networks for ECG Signals Classification Boussaa, et al. (2016). Due to the ECG signal is non-stationary signal, more complex methods for feature extraction have been conducted. Therefore, determining the best suited features is time-consuming and tedious work (Khatibi and Rabinezhadsadatmahaleh, 2019).

For deep machine learning, mass consideration is about having enough data to train the machine and turn parameters Litjens, et al. (2017), Shima, Nakashima and Yasuda (2018). Convolutional neural network (CNN) has widely been used for variance applications including ECG classification (Labati, et al., 2018), (Zubair, Kim and Yoon, 2016). They all reported that the CNN model is straightforward to apply and can improve the automatic heartbeat classification system. CNN has been used in two forms 1 and 2 directional. For instance, Kiranyaz, Ince, and Gabbouj, 2016a developed an ECG diagnosis system based on 1D-CNN and the ECG signal was fed to the 1D-CNN directly. However, for 2D-CNN, the ECG signal must be transformed into two two-dimensional forms. For instance, in Zhai and Tin (2018), a model based on 2D-CNN was proposed, where the heartbeats were transformed into dual dual-beat coupling matrix and given to the CNN model as 2-D input.

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The hybrid machine learning system is a model that consists of traditional machine learning and deep learning algorithms or a combination of two deep learning algorithms. In Khatibi and Rabinezhadsadatmahaleh (2019), CNN and kNN have participated in extracting the features. The features were later given to the SVM for ECG beat classification and arrhythmia detection. Wang in (Wang, 2020) proposed a model by combining CNN and the modified Elman neural network, and his results show that the model can improve the accuracy of the ECG beat classification system. The CNN and long short-term memory (LSTM) were examined in Oh, et al. (2018). The CNN part was responsible for extracting features and LSTM was responsible for classifying the categories of the ECG beat.

As mentioned, in most of the existing techniques, one more technique was utilized for training the features, which may affect the performance of the model. To date, no techniques exist for utilizing the kNN classifier for classifying the features without requiring to train the features. Moreover, as mentioned by Homaeinezhad, et al. (2012) and Zhang and Zhou (2005), kNN is counted as one of the well-known and fastest machine learning classifiers. Hence, utilizing it in computing any models will affect the model's accuracy and prediction. In this paper, a hybrid machine-learning model is developed for heartbeat classification. The model contains the 1D-CNN to extract the features and the kNN classifier to classify the feature signal. The CNN-kNN model is a featureless model as it does not need to have any Handcrafted features. The novelty and importance of the proposed work are that the kNN does not need further training to classify the ECG. The main contributions of the proposed model are as follows:

- Designing and implementing a high-performance ECG classification system.
- Utilizing the 1D-CNN as feature extractor.
- Using the kNN classifier for the feature classification.
- For classifying the ECG, no further training of the extracted features is required.

The rest of this paper is organized as follows. Section 2 explains the background of the area. Section 3 presents the proposed method. Section 4 presents results and a discussion of the proposed method on different tasks and a comparing it with the works in the literature. Finally, Section 5 concludes the paper.

II. Background

The traditional main steps involved in any classification system are preprocessing, feature extraction, and classifier learning. Automatic heartbeat classification is one of the applications that should follow the same process. In this paper, since the prepared data in Li and Zhou (2016); Acharya, et al., (2017a); Kachuee, Fazeli, and Sarrafzadeh (2018) are utilized, the preprocessing step is not focused on. For the feature extraction step, the 1D-CNN employed to extract the learned features which they fed the kNN classifier. In this section, a brief background about CNN and k-NN is presented.

A. k-Nearest Neighbors Classifier

kNN is one of the well-known classification methods in the world of machine learning, which is a supervised algorithm with a desirable computational speed along with acceptable classification accuracy (Zhang and Zhi-Hua, 2005). The training stage is not required for the kNN classifier but rather it is based on a simple mathematical theory (Jiang, et al., 2007). The kNN classifier imposes the lowest computational rate N compared to the most of the other classification methods, such as SVM and artificial neural networks (ANN) classifiers (Homaeinezhad, et al., 2012). Consequently, kNN is much faster than the SVM and ANN algorithms. To formulate the kNN classification algorithm, assume that the pair (x_i, $f(x_i)$) contains the feature vector x_i and its corresponding label $f(x_i)$ where $f(x_i) \in \{1,2,\ldots, n\}$ and $i = 1,2,\ldots, N$ (n and N is the number of classes and the number of train feature vectors, respectively). The principal idea behind kNN is to measure the distance between feature vectors such that the nearest neighbor for the tested sample makes a decision about the label of the features (Aljojo, 2022). The majority voting strategy among the k-nearest samples is basically adopted in this classifier. The distance for the features can be formulated in (1) Homaeinezhad, et al. (2012).

$$d\left(i,j\right)=f\left(x_i,x_j\right) \tag{1}$$

Where, $f(x_i, x_j)$ is a scalar distances function. Three common distance functions have been widely used for determining the distance as given in (2), (3), and (4) Homaeinezhad, et al. (2012).

$$f\left(x_i,x_j\right)=(x_i-x_j)^T\sum\left(x_i-x_j\right) \tag{2}$$

$$f\left(x_i,x_j\right)=(\sum_{k=1}^{p}(x_i\left(k\right)-x_j\left(k\right)))^{1/r} \tag{3}$$

$$f\left(x_i,x_j\right)=\frac{1}{p}\sum_{k=1}^{p}abs\left(x_i\left(k\right)-x_j\left(k\right)\right) \tag{4}$$

Where, Equation (2) is named generalized distance and when the weight matrix Σ = I, the famous Euclidean norm will be reached. Equation (3) is called Minkowski distance of degree r and when r = 2, again the Euclidean distance appears. Furthermore, Equation (4) is known as City Block distance and it is used in many pattern recognition cases (Homaeinezhad, et al., 2012).

B. CNN

CNN is a kind of deep neural network that was originally proposed for 2D input. It is a powerful machine learning tool for learning features from the input raw data. CNN outperforms the traditional machine learning models for image classification (Khan, et al., 2020). One of the modifications of 2D-CNNs is the 1D-CNNs, which has recently been applied in many applications (Ince, et al., 2016; Kiranyaz, Ince, and Gabbouj, 2016b; Acharya, et al., 2017b; Kiranyaz, et al., 2019). These researches have clarified that for certain applications, 1D-CNNs are preferable one-dimensional-based applications due to the low complexity, small number of hidden layers and neurons, and low cost of implementation. Typically, any CNN models are mainly composed of two parts: Feature extraction and classification. The feature extraction section is responsible for extracting features from the ECG signals automatically, which usually consists of some layers such as convolution and pooling layers, whereas the classification part is in charge of classification decisions. The classification part is identical to a typical Multi-layer Perceptron (MLP) and is often referred to as fully connected layers (Kiranyaz, et al., 2015).

The configuration of any 1D-CNN explores some important processes as shown below:

- Initialize weights and biases
- Feed forward process applies from the input layer to the output layer to find outputs of each neuron at each layer. The process is formulated in (5) (Kiranyaz, et al., 2020; Rautela, et al., 2020).

$$x_k^l = b_k^l + \sum_{i=1}^{Nl-1} \text{conv1D}\left(w_{ik}^{l-1}, s_i^{l-1}\right) \quad (5)$$

Where, x_k^l represents the input of the k^{th} neuron at layer l, b_k^l is a bias of the k^{th} neuron at layer l, s_i^{l-1} and w_{ik}^{l-1} are the output of the i^{th} neuron at layer $l-1$ and the kernel from the i^{th} neuron at layer $l-1$ to the k^{th} neuron at layer l, respectively. Moreover, $conv1D$ is used to perform the convolution process between w_{ik}^{l-1} and s_i^{l-1}.

- Backpropagation process: start from computing delta error at the output layer and back-propagate it to the first hidden layer to compute the delta errors. The Equation (6) is a delta error (Kiranyaz, et al., 2020).

$$\frac{\partial E}{\partial w_{ik}^{l-1}} = \Delta_k^l y_i^{l-1} \text{ and } \frac{\partial E}{\partial b_k^l} = \Delta_k^l \quad (6)$$

Where, E is the mean-squared error (MSE), y_i^{l-1} is intermediate output, and Δ_k^l is defined as a delta error.

- Post-process to compute the weight and bias sensitivities.
- Update the weights and biases.

III. Methodology

A. Datasets

In studies that set out to classify ECG records, authors Martis, et al. (2013a); Li and Zhou (2016); Acharya, et al. (2017b); Kachuee, Fazeli, and Sarrafzadeh (2018) used two different sources of data, namely PTB Diagnostic ECG and PhysioNet MIT-BIH Arrhythmia. Both of the sources are composed of ECG records which were recorded from different subjects; the PTB diagnostics dataset registered from 290 subjects at a sample rate of 1000 Hz (Sadhukhan and Mitra, 2012), whereas the PhysioNet MIT-BIH Arrhythmia dataset are recordings of 47 subjects at a sample rate of 360 Hz (Goldberger, et al., 2000). Table I illustrates a summary of mappings between beat annotations in five categories in accordance with the Association for the Advancement of Medical Instrumentation (AAMI) standard (AAMI and others, 1998). In this paper, the author uses ECG lead II resampled to the frequency sample of 125 Hz for MIT-BIH.

B. Preprocessing

A preprocessing for the ECG signals is performed in this work based on a set of steps as shown below:

1. Picking a 10-s window from a signal of ECG after division of the signal to 10-s windows.
2. The values of the amplitude were normalized to the range of zero and one.
3. Relying on the zero crossing of the first derivative, trace the set of all local maximums.
4. Implementing a threshold of 0.9 on the normalized value of the local maximums to find the set of ECG R peak candidates.
5. The median of the R-R time interval was considered as the nominal heartbeat period of that window (T).
6. Choosing a signal part of 1.2T length for each R-peak.
7. Unify the signal length by applying padding.

It is important to note that in the extracting R-R interval method, no form of filtering was used and to use these extracted beats as an input to the subsequent processing parts, all the beats have equal length.

C. CNN-kNN Proposed Model

The proposed model for heartbeat classification is developed based on an integration between CNN and kNN as shown in Fig. 1. The proposed model is developed based on integrating into two common machine learning algorithms, including the CNN and the kNN. The CNN

TABLE I
Summary of Mappings between Beat Annotations and AAMI EC57

AAMI class	MIT-BIH heartbeat types				
Normal beat (N)	Normal beat (N)	Left bundle branch block beat (L)	Right bundle branch block beat (R)	Atrial escape beat (e)	Nodal (junctional) escape beat (j)
Supraventricular ectopic beat (S)	Atrial premature beat (A)	Aberrated atrial premature beat (a)	Nodal (junctional) premature beat (J)	Supraventricular premature beat (S)	
Ventricular ectopic beat (V)	Premature ventricular contraction (V)	Ventricular escape beat (E)			
Fusion beat (F)	Fusion of ventricular and normal beat (F)				
Unknown beat (Q)	Paced beat (/)	Fusion of paced and normal beat (f)	Unclassified beat (Q)		

AAMI: Association for the Advancement of Medical Instrumentation

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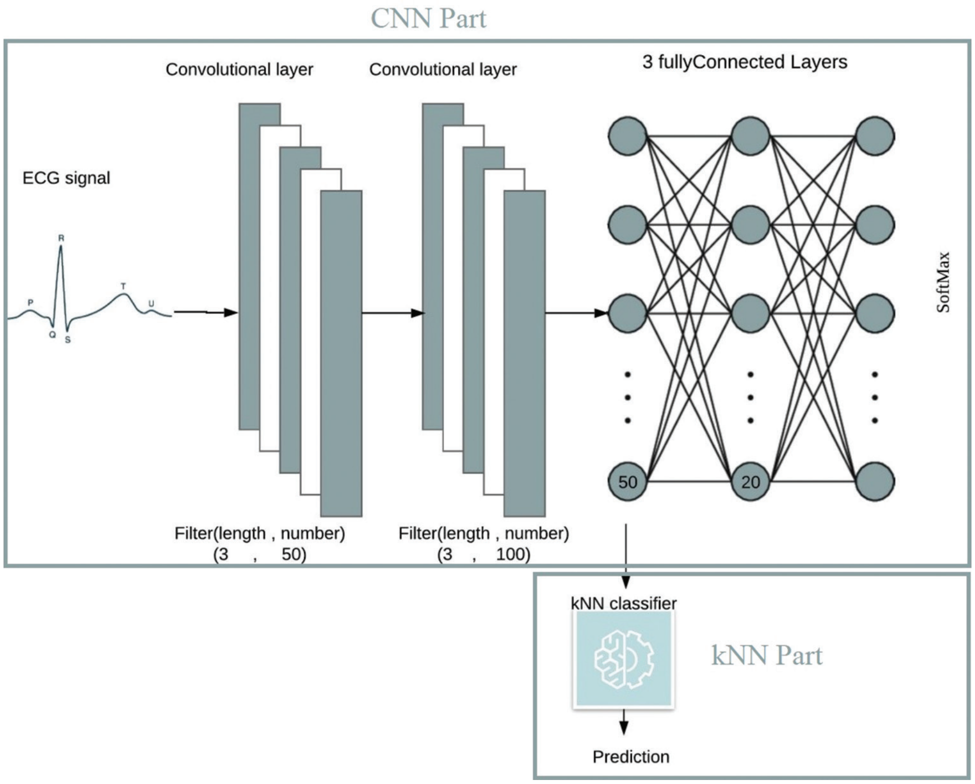

Fig. 1. Architecture of convolutional neural network-k nearest neighbor proposed model.

structure contains 8 layers including two convolutional and three fully connected layers. The number of neurons in the output layer depends on the adopted dataset (for instance, 5 neurons for PhysioNet's MIT-BIH and 2 neurons for PTB Diagnostics datasets). The other details of the CNN model can be found in Table II. In the first stage, the CNN is trained by the ECG datasets, where the hyperparameters of the CNN model were tuned using nine-fold cross-validation to get the least error rate. Then, the features are adopted from all the fully connected layers. The obtained features from each of the layers are fed to the kNN separately and the best optimum features are observed from the first fully connected layer which consists 50 nodes. In the final stage, the obtained features are classified by the kNN, where the number of k was tuned by the same strategy (cross-validation) that was used to tune the hyperparameter of CNN. In general, the CNN part of the proposed model is responsible for executing two vital tasks, which are extracting the effective features from the heartbeat signal and reducing the number of features using the fully connected layers. Moreover, the kNN part is responsible for classifying the learned features.

TABLE II
Detail of the 1D-CNN Model

No. layer	Name	Description
1	Input	187 × 1 × 1 input with 'zero center' normalization
2	Convolution	50 3 × 3 convolutions with stride [1 1] and padding 'same'
3	Convolution	100 3 × 3 convolutions with stride [1 1] and padding 'same'
4	Fully connected	50 fully connected layer
5	Fully connected	20 fully connected layer
6	Fully connected	Either 2 or 5 fully connected layer depending on the dataset
7	Softmax	Activation function for the last Fully Connected layer
8	Classification	Output cross-entropy

TABLE III
NN Parameters

Parameters	Value	Parameters	Value
Optimization method	Adam	Mini batch size	128
Initial learn rate	0.01	Number of iteration	864
Number of epochs	25	Activation function in output layer	Softmax

D. Performance Metrics

Inspired by the previous studies that have proposed models for ECG arrhythmia detection [1], [3], [7], [15], [21], [26] (Luz, et al., 2016; Oh, et al., 2018; Zhai and Tin, 2018; Bouaziz, Boutana and Oulhadj, 2019), the performance metrics that are conducted in this study include accuracy, precision, and recall. The accuracy rate shows the overall ability of the model to classify ECG signals correctly as presented in (7). Recall is the rate of correctly classified beats of one class and the total beats classified as that class. It can be calculated by (8). Precision is the ratio of correctly classified beats of one class among the total beats belonging to that class, which is formulated as (9) (Foody, 2023)

$$\text{Accuracy}=\frac{TP + TN}{TP+TN+ FP + FN} \quad (7)$$

Table IV
Accuracy of All Experiments

Dataset/layers	First fully-connected (50 nodes)	Second fully-connected (20 nodes)	Last fully connected 5, 2 nodes for MIB, PTB	Softmax layer
MIB	98	97.93	97.18	96.86
PTB	97.4	96.6	94.23	93.25

$$\text{Recall}=\frac{TP}{TP+FN} \tag{8}$$

$$\text{Precision}=\frac{TP}{TP+FP} \tag{9}$$

Where, TP is true positive, FP is false positive, TN is true negative, and FN is false negative.

E. Experiments' Setup

For any model like CNN and KNN, some parameters should be tuned to obtain the optimum values to improve the performance of the model. Regarding the kNN model, and to tune the parameter k, a 9-fold cross-validation approach is adopted. The k parameter is tuned to 5 and the metric is fixed as Euclidean distance. Following the same 9-fold cross-validation presented above, the number of convolutional layers is tuned to 2 layers, where they include 50 and 100 nodes, respectively, both with ReLu activation function. The number of hidden fully connected layers is set as two with the number of nodes equal to 50 and 20, respectively. The output layer's number of nodes is set according to the number of classes involved in the experiments. The optimization technique adopted in this network is Adam (Table III). The learned features are extracted from different fully connected layers to produce four versions of features. Consequently, four experiments per each dataset are conducted in this work as shown in the next section.

IV. Results and Discussion

To present the usefulness of the proposed model and validate the performance of each of the four versions of the learned features, four experiments per dataset are conducted and their accuracy is presented in Table IV. In both of the datasets, the same pattern of having the highest accuracy using the larger feature number is clearly seen. Learn features transformed into 50 dimensions outperform other versions of extracted features. Another observation is reducing the accuracy when the features are extracted from the softmax layer, i.e., after the softmax function is applied to the values of the features that are mapped to the output layer. This shows the non-usefulness of the softmax transformation for the kNN classifier.

The implementation of the proposed model includes two phases since the CNN-kNN method is an integrated model using CNN for extracting features and kNN as the classifier. In the first phase, an MPL-based 1D-CNN model is evaluated on PhysioNet MIT-BIH Arrhythmia dataset. Inspired by the previous works, which are cited in Table V, the dataset is set as 21892 and 87554 heartbeats for testing and training, respectively. As shown in the table, the accuracy rate of the proposed model is 98%, which is much higher compared to the second highest rate by the 1D-CNN, which is 96.8%. The reasonable accuracy of the CNN-kNN refers to the ability of the kNN classifier to classify the features of ECG. The second phase is about extracting features from the same 1D-CNN model but instead of utilizing the MLP, kNN is adopted as a classifier called CNN-kNN. The result shows that, in terms of accuracy, the ability to identify correct samples, and the quality of prediction, the 1D-CNN model and CNN-kNN model outperformed several state-of-the-art studies. It is noticeable that the proposed CNN-kNN is able to outperform the 1D-CNN as presented in Table V.

TABLE V
Comparison of Heartbeat Classification Results

Work	Approach	Accuracy (%)
Proposed (CNN-kNN)	CNN-kNN	98
CNN	1D-CNN	96.8
Kachuee, Fazeli and Sarrafzadeh (2018)	Deep residual CNN	93.4
Acharya, et al. (2017c)	Augmentation+CNN	93.5
Martis, et al. (2013b)	DWT+SVM	93.8
Li and Zhou (2016)	DWT+Random forest	94.6

CNN-kNN: Convolutional neural network-k nearest neighbor, DWT: Discrete Wavelet Transform, SVM: Support vector machine

TABLE VI
Comparison of MI Classification Results

Work	Accuracy (%)	Precision (%)	Recall (%)
Proposed (CNN-kNN)	96.78	95.9	96.26
1D-CNN	93.64	92.7	92.05
Kachuee Fazeli and Sarrafzadeh, 2018	95.9	95.2	95.1
Acharya, et al. (2017a)	93.5	92.8	93.7
Safdarian Dabanloo and Attarodi (2014)	94.7	-	-

CNN-kNN: Convolutional neural network-k nearest neighbor

MI detection is also treated as a two-class classification problem (infracted and non-infracted classes). The length of PTB diagnostics dataset is 14552 samples including 4046 normal and 10506 abnormal. Based on relevant research in the literature, k fold and hold out (20% testing and 80% training) cross-validation have been used to evaluate the utilized dataset for MI classification. In this paper, a 5-fold cross-validation is adopted. The result in Table VI shows that the performance of 1D-CNN does not surpass all the state of art results. However, the proposed CNN-kNN outperforms the state-of-the-art model performances. As shown in Table VI, the proposed model has a great ability in classifying and predicting the heartbeats compared to the participated algorithms, and the result of the accuracy metric is an evidence for this. In addition to the superior accuracy of the propose method, the CNN-kNN technique has a great prediction, which outperformed the participated models in the table. The great prediction of the proposed model is supported by the result of the Precision. The result of the Recall metric proves the ability of the model to identify high percentage of samples correctly.

V. Conclusion

This study has proposed a model for ECG heartbeat classification based on CNN-kNN models. The 1D-CNN model is used to extract the features from the ECG signal and then fed to the kNN classifier. According to the results, the proposed method is able to make predictions on both arrhythmia and MI tasks whereas outperforming the accuracies of the state-of-the-art methods in the literature. The CNN-kNN model does not require the handcrafted feature as well as no further training is needed unlike any integrated model, as the kNN classifier has no training stage. However, the proposed model still needed to be validated by various datasets in this field to be more generalized.

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