Atrial fibrillation classification using deep learning algorithm in Internet of Things–based smart healthcare system

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Abstract
Detecting the electrocardiogram pattern in Internet of Things–based healthcare system and notifying this to the user is a challenging task. Using advance computing methods for classification of electrocardiogram signal is a notable research topic. In this research work, an intelligent electrocardiogram signal classification, employing deep learning algorithm, developed and tested in Internet of Things–based smart healthcare system was proposed. For classification of acquired electrocardiogram signal, a partitioned deep convolutional neural network was proposed. The electrocardiogram feature continuously in the Internet of Things–based monitoring system was learnt. To make use of learned features in the continuous time series data, it forms a higher order space in the server. We have made quantifiable comparative analysis with other classification algorithm with the same time series data collected from different atrial fibrillation samples in the Internet of Things–based e-health system. Our proposed algorithm learned features were tested in atrial fibrillation classified signal with other conventional classifiers with various performance indices. We obtained an accuracy of 96.3 percent with 93.5-percent sensitivity and 97.5-percent precision. From the obtained result, processing with proposed deep convolutional neural network provides reliable timely assist and accurate classification of electrocardiogram signal in Internet of Things–based smart healthcare system.

Keywords
deep learning algorithm, electrocardiogram signal processing, healthcare system, smart medical informatics

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Introduction

In the current societal scenario, the death count in terms of heart attack is an increasing one. In particular to a number of cardiac failures, the worst case is atrial fibrillation (AFib), and it is responsible for 65–80 percent of reported heart attack cases. During AFib, the electrocardiogram (ECG) rhythmic pattern of heart signal gets altered. It lasts by change in QRS complex, missing of U-wave, and PR interval change occurs. This has to be immediately detected and treated.

From the advent of modern healthcare system, the use of intelligent sensor in wireless sensor network (WSN) and advanced computing technology makes the transmission of things in a secured wireless private network (WPN) channel possible. By the mobile Internet concept, the smart health monitoring system plays a vital role. Many hospitals follow their own applications (apps) for patient monitoring and consulting. This makes the presence of point of service in fingertips. The database for healthcare record keeping is modified into electronics form in a secured server.

However, continuous data acquiring and transmission by intelligent sensor results in accumulation of large volume of data. In this kind of system, the three big data V’s are represented as the following: (1) Volume of data—The designed architecture for the wearable sensor continuously monitors the patient’s physiological signal like ECG in large volume. (2) Variety of data—ECG signal is a time-varying signal. This kind of signal is originated from heterogeneous and unstructured data source; hence, the nature of signal depends on several parameters. (3) Variability of data—ECG signal is a complex non-deterministic signal. Hence, these kind of data can change with time. Hence, the enormous amount of time series data form huge data for a system to handle.

By the implementation of highly sophisticated algorithm for processing, also from the available standard ECG pattern, this computing algorithm can perform the training of their network from the presented input features. Then, it processes in predicting the feature in the testing phase and classifies the presented input signal. Compared to conventional machine learning algorithm–based classifier, the deep learning methods of classifier have increased classification accuracy and are highly precise in pattern classification.

The important aspect of this research article is organized into three aspects as the following:

- ECG signal in Internet of Things (IoT) based smart healthcare system was obtained, and the dataset is formed in lvm format file using myDAQ.
- Then, feature in ECG signal for training the 7-layer convolutional neural network (CNN) for training was computed.
- Finally, the trained neural network is used for testing the remaining ECG dataset in the testing phase.

To validate the above task, the learning and classification accuracy, error, and precision for other conventional classifiers like support vector machine (SVM) and autoencoder for verification were compared. For this implementation, a sample ECG feature is described in Figure 1. The represented feature was used for training of proposed deep CNN model. From this normal feature and the affected AFib ECG waveform, the value of PR interval, QRS complex interval, and presence of U wave is considered for identification of AFib ECG signal. Application of the proposed research work is to develop an advanced IoT-based ECG signal classification system to assist healthcare service provider and to form a consumer electronics for ECG classification.
used for developing dataset in IoT healthcare system, and deep CNN architecture for learning is showed. Section “Experimental verification of deep CNN model” presents the experimental implementation of proposed CNN algorithm in myRIO processor with a hardware setup. In section “Results and comparison of performance index for verification,” performance evaluation by various performance indices is compared, and in section “Conclusion,” the conclusion of this research work is given.

**Review of related work in ECG classification**

In this section, we recapitulate some recent research activity related to ECG data analysis using deep learning models for signal classification.

In Teijeiro et al.,¹ they proposed an ECG signal classification scheme based on the implementation of abductive interpretation of ECG data. In this work, they explain about the needed features for ECG signal classification parameter to be measured. From this work, the nature of ECG parameter for feature prediction was known. In Li et al.,³ they explained the nature of deep learning model and its need for performing data analysis. Also, in this paper, the characteristic of IoT device and nature of intelligent sensor was explained. The usage of deep learning model for data analysis and advantage of deep learning algorithm over machine learning algorithm were identified.

In Lin et al.,⁷ they implemented a deep neural network model for electrocardiography data classification. The author explains how the time series data are used to form dataset for training and testing of deep neural network. From this work, it was understood how dataset was formed for training and testing a deep neural network, also how to form batch of data from large volume of data available. In Sopic et al.,⁹ the SVM-based classification of ECG signal in a remote healthcare system is explained with various performance indices. From this work, various performance indices used to evaluate the performance of classification algorithm were identified. Hence, the classification algorithm is needed for forming dataset and interpreting the large volume data in the modern remote healthcare system. In Xia et al.,¹⁰ they explained the wearable device for IoT application. Then, they explained about automatic cardiac arrhythmia classification based in ECG signal. The signal transmitting module in the patient node with secured channel is explained from this architecture, and we came to know how to include the security concept for the transmitting of signal.
From this, we came to inference that most of the research work is based on ECG signal classification from the extracted data and learned using offline feature extraction. Now, we change the feature extraction in training with testing of extracted ECG signals in IoT-connected smart healthcare system without an expert’s knowledge. From the trained network, we can predict the remaining sequence in the batch of dataset and alert the user for AFib ECG pattern.

Materials used and methodology followed

**ECG signal extraction using NI-myDAQ in IoT healthcare system**

In this work, we used National Instruments myDAQ signal acquiring hardware connected to an intelligent ECG electrode in the patient wearable unit. In the IoT-based connected environment, large volume of data have been acquired, and the acquired signal is processed and conditioned for transmission in secured wireless channel. Hence, the signal is collected in the patient side and is transmitted to base station. The processing is performed in base station. The latency of signal is kept low for this. The main characteristic of this medical IoT device is it consumes low power and has high mobility.

To acquire patient signal, BPL-CECL 3 channel ECG machine as a patient intelligent sensor was used. This was connected to NI-myDAQ hardware for signal conditioning. The real-time processing is possible in NI-myDAQ since it has inbuilt signal conditioning circuit and isolation from the noise signal generated. Due to noise in measurement at the patient WSN in the patient node, edge computing to provide data interface in patient node and base station was performed. The architecture of IoT-based connected healthcare system is shown in Figure 2. From the architecture the flow of signal from the patient node to the processing node provides wireless communication using a WPN.

We utilize the use of National Instruments hardware to connect with the smart healthcare system, which provides the following advantages:

- Higher connective range in secured WPN.
- Less energy consumption.

![Figure 2. Schematic illustration of ECG classification application followed in IoT-based smart healthcare system.](image-url)
Inbuilt signal conditioning system.
Low latency with real-time processing.

The monitoring graphical user interface (GUI) for patient is provided by LabVIEW front panel design. This indicated immediate alert and warning graphically.

This received signal sampled at 500-Hz sampling frequency, 24-bit resolution, 24,000 sample length with LabVIEW measurement file format (.lvm). This lvm file is used for processing in deep learning algorithm. The format of lvm does not affect the time series ECG data. First 20 normal sequences are used for training, and remaining sequences can be tested from the pattern.

**CNN structure for ECG feature learning and classification**

CNN is a fully connected layer which has two major layers such as convolutional and pooling. The main use of these two layers is the following:

- The convolutional layer detects features in input dataset with learnable vectorized kernel $K_n^{ij}$.
- The pooling layer reduces the computational complexity by identifying spatial–spectral relation in the dataset. It downsamples the presented input.

The combination of convolution and pooling makes the CNN a fully connected network. Hence, deep CNN network can provide solution to parameter overfitting problem. The same weights are shared in the layer by weight-sharing procedure. The convolution of feature is associated with associated weight of the layer. The kernel vector is obtained by the use of activation function.

The design parameter for the proposed deep CNN network is presented in Table 1. The input is presented in the input layer by the pre-processed signal from NI-myDAQ connected to the intelligent sensor. The output layer has two neurons, which correspond to two possible outputs in the ECG signal monitoring system, such as the AFib ECG pattern and normal ECG pattern. The weight of network is initialized between 0 and 0.05. For training dataset, 20 batch size time series data for 20 epochs are considered, and for testing interval, 100 epochs for every 10 iterations are considered.

Hence, in this proposed research work, a 7-layer regression CNN was used. It consists of an input layer, two units of a convolutional layer and max-pooling layer, fully connected layer, and output layer. The architecture of the proposed deep CNN network for a smart hospital with design parameter is given in (Figure 3). The training and testing of ECG pattern is obtained by presenting

| Layer | Type                     | Neuron in layer           | Kernel size |
|-------|--------------------------|---------------------------|-------------|
| 1.    | Input                    | 7 maps with 127×127 neurons | 11×11       |
| 2.    | Convolution C1           | 256 maps with 7×7 neurons | 7×7         |
| 3.    | Max-pooling M1           | 256 maps with 7×7 neurons | 7×7         |
| 4.    | Convolution C2           | 256 maps with 7×7 neurons | 5×5         |
| 5.    | Max-pooling M2           | 256 maps with 7×7 neurons | 5×5         |
| 6.    | Fully connected FC       | 4096 neurons              | 3×3         |
| 7.    | Output                   | 2 neurons                 | 1×1         |

CNN: convolutional neural network.
input in the visible input layer. This is connected to a $7 \times 7$ convolutional layer and a $5 \times 5$ subsampling layer. Then, the fully connected layer corresponds to the output of one pattern trained.

**Deep CNN model training phase**

The proposed deep CNN is a supervised feature training, since ECG signal dataset is standardized and used for training this 7-layer deep CNN. Moreover, a CNN regression stochastic algorithm (RSA) was followed for classification. In the IoT-based healthcare, continuous time series data are collected; hence, batch training model is used for deep the CNN RSA model. The two pair convolutional layer is of the form

$$x_{ij} = f \left( \sum_{i=0}^{n} K_{ij}^l + b_{ij} \right)$$

where $K_{ij}^l$ is the kernel computed for the entire training dataset by equation (1). Here, $f$ is the non-linear function, $K_{ij}^l$ is the kernel in the convolutional layer, $i$ is the input layer, and $j$ is the output layer

$$K_{ij}^l = I_{ECG}(t) + M_{\sigma} + N(a,b)$$

Here, $I_{ECG}$ is the standard ECG dataset at time for training data. $M_{\sigma}$ denotes the kernel distribution, and $N(a,b)$ is the random noise in training data. The tuning of parameter $(a,b)$ is obtained by negative log-likelihood function, which is given by

$$N(a,b) = -\sum_{i=0}^{N} \log P(X = x_i; \theta)$$

where $N$ denotes the number of training dataset used.
The generalized loss function is used to avoid overfitting problem, which is given by

$$P(\theta, N) = N(a, b) + \varphi R(\theta)$$  \hspace{1cm} (4)$$

where $R(\theta)$ denotes the $L_2$ norm value and $\varphi$ controls the design layer weight. Hence, the maximum value of $P(\theta, N)$ is used for getting high accurate training of our CNN model. The ECG training system structure by deep CNN algorithm is shown in Figure 3. In the 20 batches, ECG dataset from intelligent sensor presenting to the input layer is shown. In the architecture, the convolutional and max-pooling of two sets of C1-convolutional and M1-subsampling layer signal training and pattern identification in fully connected layer are shown.

**Experimental verification of deep CNN model**

In the testing of ECG pattern extracted, same time series dataset described in section “ECG signal extraction using NI-myDAQ in IoT healthcare system” is presented in the input layer in trained deep CNN. This experiment was conducted in the following workstation server intel i7 processor, 64GB RAM with NVIDIA graphic GPU, 1TB hard disk. The performance indices are measured in MATLAB and signal acquisition is done in LabVIEW package in the (.lvm) format.

**Implementation of proposed CNN**

The supervised learning CNN has backpropagation of error architecture for minimization. Algorithm 1 explains the training and testing procedure for the given training data ($x_i, y_i$) in the prescribed workbench. In the algorithm, the following parameters $\Delta W^{(l)}$ and $\Delta b^{(l)}$ are obtained, which are tensors of the same vector. From Algorithm 1, the forward pass of ECG signal and backpropagation of error with each change in layer change in weight.

For this Algorithm 1, the dataset is divided by training dataset for 20 batches of normal ECG data pattern. For remaining signal from subjects, it can be normal or AFib pattern ECG. Since in the IoT smart healthcare system the intelligent sensor continuously sends signal to server, the 20-batch signal divides this acquired lvm format time series data into each 2-min record of 50 samples. Hence, the time series data to the batch of 50 sample dataset for training and testing in the server were partitioned. Figure 4 shows the entire system with signal extraction using an intelligent sensor, data processing using a $7 \times 7$ deep CNN network, and data visualization in patient GUI. Also, the provision for smart hospital service provider to see the patient ECG data for validation is provided. This network consists of C1-first convolution layer with M1-subsampling layer and C2-second convolution layer with M2-subsampling layer.

**Implementation in other classifier for verification**

As stated earlier, this article investigates ECG classification by a proposed deep CNN model in IoT-based healthcare system. Hence, to validate this deep CNN architecture with another classifier, the architecture proposed by SVM and deep autoencoder was evaluated.

**Experimental implementation on SVM classifier.** To verify the performance, first, the dataset of 20 batch training presented on SVM classifier was implemented. The kernel value computed for the output vector is calculated, and the testing accuracy of 84.5 percent was obtained with a regularized value of $\Delta w = 0.652$. This result is tabulated in Table 4. It is noted the Gaussian SVM has a low
Algorithm 1. Pseudocode for training by proposed deep CNN.

1: Input: $X_i, Y_i$ where $i=1,2,...,n$, threshold $\mu$, number of block layer $l$, regularization $\lambda$.
2: Output: $P(\theta,N) = W, b, \theta, N$
3: for $i=1,2,..,n$ do
4: if type = convolution then
5: $Z_y = K_y^{(l)} * a_i + b_j$
6: Output $K_y = f(K_y^{(l)})$
7: if type = pooling then
8: for $i=1,2,..,n$ do
9: $X_s = pooling(X)$;
10: $Z_y = \mu X_s + b$;
11: Output $Z_y = f(K_y^{(l)})$
12: if type = fully connected then
13: $P(\theta,N) = N(a,b) + \lambda R(\theta)$
14: end for
15: reweight $P(\theta,N)$
16: end for

Figure 4. ECG data transmission in IoT-based healthcare system and processing of using proposed deep CNN network with C1-first convolution layer with M1-subsampling layer and C2-second convolution layer with M2-subsampling layer.

accuracy when compared to the $7 \times 7$ deep CNN, and we obtained the error of 14.78 percent in the testing phase for 50 samples lvm format time series data.
Implementation of deep autoencoder network. To verify the performance, the ECG dataset acquired by the IoT-based healthcare system in deep autoencoder\(^{14}\) was implemented. This autoencoder network consists of one input layer and one output layer. It is a fully connected network with the same weight shared with layers. Hence, the input layer to the output layer and all the layers are fully connected. It learns and reduces reconstruction error by latent representation in the stacked autoencoder greedy wise. The learning rate is of 0.85 and convergence is up to 100 epochs. This results in long training time. Pretraining of dataset is performed to increase the accuracy. It has an accuracy of 91.5 percent as increased by SVM but lower than that of the proposed deep CNN network in IoT healthcare monitoring system. The obtained result was presented in Table 4. In deep autoencoder model, the testing calculation is reduced to 6.5 percent, but the learning time is increased when compared with SVM classifier and proposed deep CNN architecture.

Results and comparison of performance index for verification

The performance assessment of the proposed 7×7 deep CNN algorithm is performed by metrics\(^{15}\) like accuracy, specificity, sensitivity, training time, and classification error. The evaluation of the proposed classifier algorithm and other classifier with the same 20-fold validation approach was carried out. First, with normal ECG, time series data of 10 sequences are used to train the network and the next 10 sequences are used as testing of ECG signal for classification of AFib. The training time and testing time curve are shown in Figure 5 for the proposed deep CNN network and the
verification classifier. From the classified ECG signal, confusion matrix using the conditions was computed:

1. If the normal ECG signal is classified as normal patient ECG in the testing phase, then it is true positive; otherwise, it is false positive. For true positive, the PR interval is 120–180 ms, QRS complex have 75- to 100-ms duration, and U wave presence is clearly visualized in patient GUI and service provider monitoring system.
2. For false negative, the AFib ECG pattern is classified as AFib patient ECG; then, it is true negative; otherwise, it is false negative.

From the Advancement of Medical Instrumentation system (AAMI) standards, the following specifications were followed for ECG signal training. The feature employed for training the proposed deep CNN model in IoT-based healthcare system is explained in Table 2. Other time domains not listed are also considered for accurate training of network. In Table 2, it was identified that for training, 1100 dataset iterations were used and for testing, 400 dataset iterations were used for normal ECG pattern.

| ECG pattern         | Total set count | Training dataset count | Testing data count | Values of feature in normal and AFib pattern |
|---------------------|-----------------|------------------------|-------------------|-----------------------------------------------|
| Normal ECG pattern  | 1500            | 1100                   | 400               | RR interval: 0.6–0.8 s; QRS complex peak: less than 0.12; PR interval: between 0.12 and 0.2 s |
| AFib ECG pattern    | 1100            | 800                    | 300               | RR interval: 0.9–1.2 s; QRS complex peak: 0.1–0.4 s; PR interval: 0.2–0.35 s |

ECG: electrocardiogram; AFib: atrial fibrillation.

From this number of true prediction and AFib patient data prediction, the accuracy, precision, and sensitivity are given by following equations (5)–(7)

\[
\text{Accuracy } A = \frac{N_{TP}}{N_{TP} + N_{FN}} \tag{5}
\]

\[
\text{Precision } PR = \frac{N_{TP}}{N_{TP} + N_{FP}} \tag{6}
\]

\[
\text{Sensitivity } SE = \frac{N_{TP}}{N_{TP} + N_{TN}} \tag{7}
\]

For all the classifiers, the classification error and training time are obtained from the deviation from the testing dataset. For validation of the network, the design parameter described in Table 2.
The training time and testing time of SVM, deep autoencoder, and proposed CNN classifier are shown in Figure 5. It can be seen from Figure 5 that the training time of the CNN network is 2.6 s and testing time is 4 s, which is much less than that of SVM and deep autoencoder. From the total number of epochs, the training and testing error calculated is based on difference. From Figure 5, it is noted that the training time is reduced at the epoch 2 for the proposed deep CNN network. But for other classifier, after epoch 8, only the training and testing time got reduced. This shows the learning and classification of ECG signal in IoT-based smart healthcare system is fast and accurate by the deep CNN network.

Also, from the comparison of classifier training and testing time, it was observed that CNN has lesser training time in the network training phase. This is due to the multi-dimensional nature of CNN architecture. Table 3 shows the error rate of training and testing phase for SVM, deep autoencoder, and proposed deep CNN for the same kernel size and number of epochs with the same dataset.

By the implementation of the proposed CNN network as an ECG signal classifier, the accurate and low error rate is obtained. These values are presented in Table 4. It can be seen from Table 4 that accuracy is increased by 4.8 percent by comparing with deep autoencoder. This makes the ECG prediction accurate for the user without the knowledge of service provider. The true value classification error is identified to be low as 0.21. This makes the synchronization of data with the entire system.

The graphical comparison of various ECG classification methods by their accuracy is shown in Figure 6. The proposed 7×7 layer CNN classifier classifies ECG data in the IoT-based

### Table 3. Comparison of training error and testing error for kernel size = 20 and epoch = 10.

| Kernel size | Training error rate | Testing error rate |
|-------------|---------------------|--------------------|
|             | SVM | Deep autoencoder | Proposed method | SVM | Deep autoencoder | Proposed method |
| 1           | 5.7 | 5.3              | 2.6              | 18  | 9.2              | 4                |
| 2           | 5.4 | 5                | 2.1              | 14  | 8                | 3.6              |
| 3           | 5.2 | 4.8              | 1.6              | 12.5| 7.2              | 2.8              |
| 4           | 4.8 | 4.2              | 1.2              | 11  | 6.5              | 2                |
| 5           | 4.2 | 3.6              | 0.9              | 10.9| 5                | 1.9              |
| 6           | 3.2 | 3                | 0.4              | 8.2 | 3.5              | 1.6              |
| 7           | 3   | 2.7              | 0.2              | 6.5 | 3                | 1.2              |
| 8           | 2.4 | 1.3              | 0.1              | 5.1 | 2.6              | 0.7              |
| 9           | 2   | 0.9              | 0.1              | 4.2 | 2.2              | 0.1              |
| 10          | 1.8 | 0.8              | 0.1              | 3.1 | 2.2              | 0.1              |

SVM: support vector machine.

### Table 4. Performance comparison of SVM, deep autoencoder, and proposed deep CNN for data of batch size = 20, learning rate = 0.09, and epoch = 100.

| Methods                | Author, year | PR (%) | SE (%) | A (%) | Training time in seconds | Rate |
|------------------------|--------------|--------|--------|-------|--------------------------|------|
| SVM                    | Bono et al.,14 2016 | 94.1   | 75.8   | 86.4  | 3.5                      | 0.34 |
| Deep autoencoder      | Yu et al.,16 2018 | 90.5   | 82.4   | 91.5  | 4.5                      | 0.21 |
| Proposed CNN network  | Proposed method | 97.5   | 93.5   | 96.3  | 2.1                      | 0.14 |

SVM: support vector machine; CNN: convolutional neural network; PR: precision; SE: sensitivity; A: accuracy.
healthcare system. It has a high accuracy of 96.3 percent as compared with SVM classifier and deep autoencoder. From the graphical comparison of accuracy shown in Figure 6, ECG pattern classification in the IoT-based smart healthcare system by the designed deep learning algorithm was verified.

**Conclusion**

In this research article, a novel classifying technique using deep learning CNN architecture in IoT-based smart healthcare system was proposed.

- The proposed deep learning algorithm is able to process high amount of continuous time series ECG signal acquired by an intelligent ECG sensor connected to the healthcare system.
- As a case study, comparison of various classifier algorithms such as SVM classifier and deep autoencoder for the same ECG data was performed.
- The effectiveness of the proposed algorithm is verified by the obtained experimental results. Moreover, network training time and testing time were verified by the same batch size of dataset with other techniques also.
- Hence, from the obtained result, the proposed deep learning algorithm makes ECG pattern classification user-friendly in the user end side and service provider side in the IoT-based smart healthcare system.

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