An Internet of Things (IoT) Homecare Management System Using Cardiac Arrhythmia Classification

Areej Almazroa*, Hongjian Sun†

*Department of Computer Sciences, King Saud University, Riyadh, KSU, 11543
*†Department of Engineering, Durham University, Durham, UK, DH1 3LE
Email: *aaalmazroa@ksu.edu.sa, †hongjian.sun@durham.ac.uk

***Abstract*—Due to the fast growing of population, a lot of hospitals get crawdad from the huge amount of patients visits. The need for providing patient care while they are at home at anytime is important and the era of homecare should started. Internet of Things (IoT) is widely known and used by different fields. IoT with the assist of homecare will help in reducing the burden upon hospitals. IoT with homecare bring up several benefits such as minimizing human exertions, economical advantages and raising in efficiency and effectiveness. The most important feature in homecare system is the accuracy because those systems are dealing with human health which is sensitive and need high amount of accuracy. The trusted homecare system by health experts should be able to detect abnormalities and make decisions in an accurate way that reaches 100%. To overcome the accuracy limitation, this paper presents a Cardiac Arrhythmia monitoring framework. Cardiac Arrhythmia happend when the Electrocardiogram (ECG) signal contains irregularity in their features. The raw ECG Signal is passed through signal processing stage to clear it from noise. Then the cleared signal is passed through the feature extraction stage to extract a number of features that are used in the classification stage. After that, a classification stage to detect Cardiac Arrhythmia is made using deep learning to raise the accuracy. Based on experiment results, the proposed model is more accurate in the classification of Cardiac Arrhythmia and more reliant from caregivers point of view in comparing with other researches.**

***Index Terms*—Internet of Things (IoT), homecare, healthcare, Electrocardiogram (ECG), Deep Learning.**

I. Introduction

Nowadays, homecare management systems are very serious because of the growing number of patients in hospitals. Having those systems with IoT will extend more to the homecare. With the assist of communication technologies and using IoT sensors and actuators, caregivers can observe their caretakers remotely. Furthermore, based on the sensor data, various decisions can be applied to minimize the load of caregivers.

Heart is the extreme serious organ in the human body that requires high range of caring and monitoring. However, homecare monitoring systems that deal with that organ are rarely used because of the accuracy shortness.

An IoT monitoring system was presented in [1]. Body sensors gathered ECG and vital signs and sent them to the cloud using Bluetooth communication technology. The ECG signals were filtered using various signal processing techniques. To enhance the security, watermarking was used before sending the signal to the cloud. The feature extraction stage was made in the cloud. Support Vector Machine (SVM) classifier was used for the diagnosis. The classifier output was sent to the caregivers for decision making. Then the final decision was sent to the cloud. Simulation results showed that the classification accuracy was 83% which is low and needs to be raised by developers.

Another real time ECG tele-monitoring system was presented in [2]. An advanced alarm system was used to prevent unexpected cardiac arrests. A monitoring device was placed on the chest and connected using Bluetooth to a smart phone. Then the monitored ECG signals were sent in real time to the cloud using cellular network. Five volunteers nominated in evaluating the system showing reasonable ECG measurement with a full centralized monitoring.

Moreover, Yang *et al.* [3] presented an IoT ECG monitoring system using wearable sensors. Using IoT and cloud, a new ECG monitoring way was proposed. the wearable sensors were responsible to collect the ECG signals and sent them to the cloud. The communication technology used was WiFi. When the data sent to the cloud it can be stored for analysis. To let the users access the data anytime and anywhere, cloud used two protocols Hyper Text Transfer Protocol (HTTP) and Message Queuing Telemetry Transport (MQTT) protocol. For evaluation, a volunteer person was nominated for reliability testing. In collecting and presenting the system was reliable.

Furthermore, Mahdy *et al.* [4] proposed an IoT Arrhythmia detection system using an ECG holter device. The real time ECG signals were taken from an ECG sensor located on the patient's chest. The sensed data was sent to a smart phone using Bluetooth communication technique. The data then classified to normal and abnormal using machine learning algorithm called K-Nearest Neighbors (KNN). The system was evaluated in terms of classification accuracy using 303 patients. The evaluation result was 70% for the classification accuracy which is very low.

Our aim is to design an IoT homecare system using cardiac arrhythmia classification for monitoring patients remotely to support comfort living. The proposed model will make feature extraction and classification for arrhythmia detection purpose using one of the deep learning algorithm. The accuracy of the proposed model will be raised due to the using of deep learning which make it reliable for best remote arrhythmia detection.

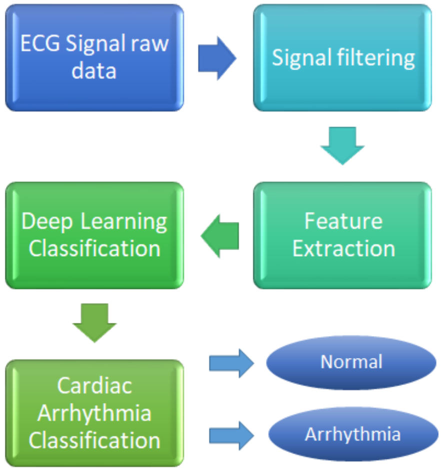

Fig. 1. Model Operations

This paper makes two significant contributions:

- Design a Cardiac Arrhythmia classification model for arrhythmia detection that contains of feature extraction and classification stages.
- Use deep learning algorithm for classification to increase the accuracy of the model.

The paper is organised as follows: In section II, we provide a detailed description of the considered methodology. In section III we present the simulation parameters and discuss the experiment results.

II. Considered Methodology

We will consider an IoT cardiac arrhythmia detection system. First, we will present the framework for feature extraction and classification using online database. Second, we will apply deep learning algorithm to increase the accuracy. The main model operations are described in Fig.1.

We will focus on implementing a cardiac arrhythmia model. The ECG signals used in this model are downloaded from an online database and stored in the local storage. The ECG signals are filtered using signal processing techniques. Then several features will be extracted from those signals. Deep learning will be used in the classification stage to raise the accuracy.

A. ECG Signal

Each cycle of ECG signal consists of five main waves as shown in Fig. 2:

- P wave: the sequential activation (depolarization) of both atria.
- Q wave: the downward deflection immediately preceding the ventricular myocardium.
- R wave: the peak of the ventricular myocardium.
- S wave: the downward deflection immediately after the ventricular myocardium.
- T wave: ventricular repolarization.

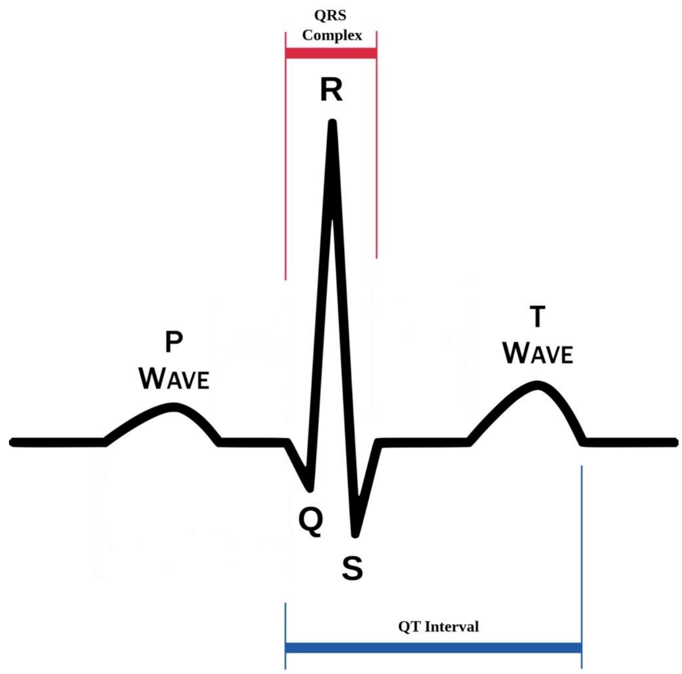

Fig. 2. ECG signal components

B. Signal Processing

Filtering is a type of signal processing techniques that is used to remove the noise. This preprocessing step is essential for accurately detecting the waves in the ECG signal. Doing this step is very important to raise the accuracy of monitoring and diagnosing. A low-pass filter is one of the filtering technique used to enhance the signal and to reduce the noise. It worked by minimizing high frequency components from the signal and also to remove external interference to avoid artifacts. The unsuitable use of that filter may cause misdiagnosis. Low-pass filter is worked by putting the signal in lower frequency then attenuating the signal with higher frequency.

C. Feature Extraction

The clean and clear signals arrived from the signal processing stage and ready for the feature extraction. The peaks and waves can be marked clearly and the interval between those waves are important in detecting abnormality. Several features of ECG signal can be extracted using the waves and peaks marked. The specification of those features are [5]:

- QRS Complex: the time interval between Q wave until reaching S wave in milliseconds.
- RR interval: the time interval between two adjacent R waves in two followed cycles in milliseconds.
- Heart Rate: calculated by dividing 60 over the RR interval in beat per minute (bpm) as expressed by eq(1).

$$HR(bpm) = \frac{60}{RRinterval} \tag{1}$$

- QT interval: the time interval between the start of Q wave and the end of T wave in milliseconds.

D. Classification using Deep Learning

The classification and detection of our framework are made using deep learning. Deep learning algorithms are part of the machine learning that belongs to Artificial Intelligent technique. In our model it is used in raising the accuracy of arrhythmia detection and minimizing the human efforts. Deep learning is different from machine learning in the presentation of data. It depends on number of layers of Artificial Neural Network (ANN). ANN is a connected nodes called artificial neurons based on the biological brain neurons. However, neurons in ANN are static and symbolic. A feedforward neural network is a type of ANN where the connection between neurons do not support any backward results as an input so they don't form a cycle.

A **Multilayer Perceptron (MLP) neural network** is a class of a feedforward artificial neural network. MLP used in this framework as a classifier for best cardiac arrhythmia detection. MLP can differentiate data that are not separated linearly. It consists of four components: input layer, hidden layers, output layer and weights between them. Weights can be found using derivative, partial derivative or chain rule. When chain rule is applied to find and update the weight, this is called backpropagation. Three types of activation/loss functions can be applied on neurons: piecewise linear, sigmoid or signum.

MLP works as follows:

1) Weight initialization
2) Inputs application
3) Sum of inputs - weight product
4) Activation function calculation
5) Weight adaption
6) Back to step 2

III. Experiment Results

A. Simulation Setup

For simulation parameters, the ECG data was downloaded from PhysioBank.com. The first 48 ECG signals were taken from MIT-BIH Arrhythmia database [6]. The signals were taken between the years 1975 and 1979. They were related to patients in and out the hospital. The last 18 signals were taken from MIT-BIH Normal Sinus Rhythm database. No arrhythmias were found in this database that was taken from 5 men and 13 women. The signals in those database are made of half an hour recording from Holter device in labs [7], [8]. The raw signals in both database were digitized in the hospital at 360 samples per second per channel. The platform used for this simulation model is built using MATLAB simulation environment version R2019a. The device used is a desktop personal computer with Intel Core i7 processor.

B. Simulation Results

The online database was downloaded and saved in a local storage and ready to be used by the simulation. All the 66 signals were passed through the simulation and presented in samples per amplitude as shown in Fig. 3. Each signal need to be enhanced using the implemented low-pass filter to remove the noise as shown in Fig. 4.

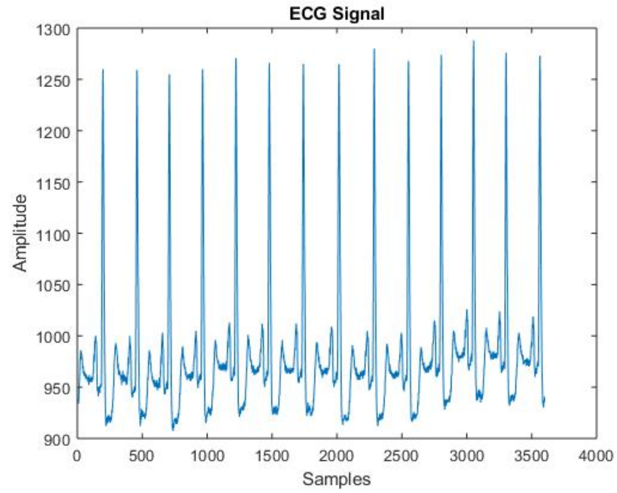

Fig. 3. Raw ECG signal

After enhancement, the signal passed through the feature extraction stage. The five main waves and peaks were marked as shown in Fig. 5. Red triangles represent the highest peaks while green squares represent the bottom. The rest of peaks were marked based on the starting of each wave.

After that, the cleared signal is passed through the feature extraction stage. Using the peaks and waves on the cleared signal, several features can be extracted.

The most important features in our work are QRS and heart rate. Those two features were extracted from all the 66 signals and saved in a file in the local database of the computer running the simulation to apply the classification on them.

For cardiac arrhythmia classification a deep learning MLP feedforward artificial neural network was implemented to learn the mapping between inputs to predict output. This type of deep learning algorithm is able to determine the data that are not separated linearly. A sigmoid was used as an activation

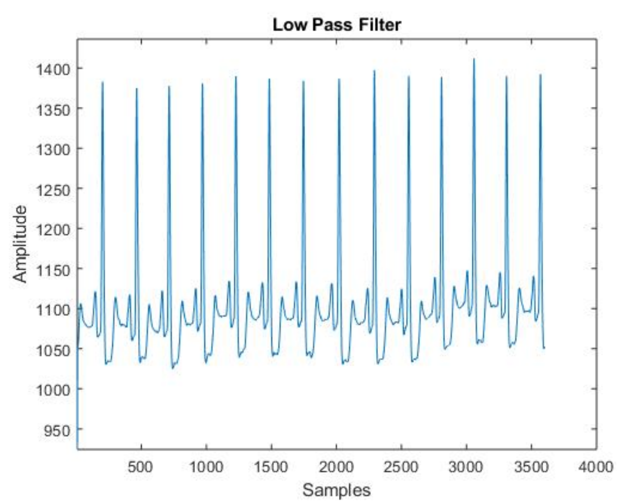

Fig. 4. Effect of Low-Pass filter

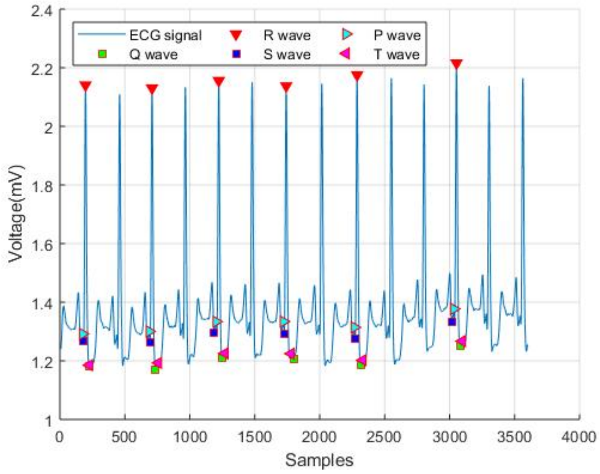

Fig. 5. ECG Signal Peaks

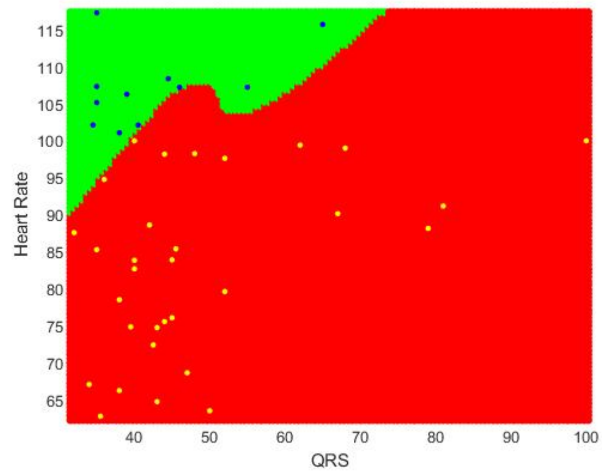

Fig. 6. Decision boundary

function as expressed by eq(2), where x is the weighted sum of inputs.

$$Sigmoid(x) = \frac{1}{(1+e^x)} \quad (2)$$

Backpropagation algorithm was implemented for training with a gradient descent to find the best weight as expressed by eq(3), where K is the training iteration, C is the learning rate and E is the loss function.

$$w_{l_j}^{k+1} = w_{l_j}^{k} - C\frac{\partial E}{\partial w_{l_j}} \quad (3)$$

The loss function can be expressed by eq(4), where t is the target output, y is the actual output and n is the training data.

$$E = \frac{1}{2n}\Sigma_{i=1}^{n}(t-y)^2 \quad (4)$$

Train by Epoch was used to keep all the parameters fixed and calculate the weight using all the training data then accumulate them and update the parameters once. For training, 80% of total data was used while the remaining 20% for testing. Two features were selected as input; heart rate and QRS and two outputs; normal and Arrhythmia. The number of hidden layers in the neural network were two each one of them contains 10 neurons. The learning rate selected to be 0.15 and the maximum number of epoch is 500. Mean Square Error (MSE) was selected as an evaluation metric to measure the average squares classification errors and can be expressed by eq(5).

$$MSE = |\frac{\Sigma_{i=1}^{n}(t-y)^2}{n}| \quad (5)$$

The decision boundary for the values of the two features QRS and Heart rate are displayed in Fig. 6. In this figure four colours are used. Yellow dots represent the normal values while blue represent the abnormal values. Red and green are clearly differentiate between the two classes by drawing a wave decision boundary. The MLP algorithm was able to classify the data into normal and Arrhythmia and draw a non linear decision boundary between them after 176 epochs done out of 500 with a MSE reaches 0.019 which is very close to zero.

The MSE is calculated and displayed based on the number of epochs reached as shown in Fig. 7. For the first 10 epochs it was 0.31 and then 0.09 after 100 epochs. Finally it reaches 0.019 after 176 epochs which means very high accuracy.

To compare the results with previous work. MLP algorithm was applied with Backpropagation technique using the same database from PhysioBank.net and details can be found in Table I. The parameter values were taken from the research paper in [9]. The learning rate selected to be 0.002 and the maximum number of epochs was 1000. Four hidden layers were used with 60 neurons in each one of them. Normalized MSE (NMSE) and accuracy were used as evaluation metrics as expressed by eq(6) and eq(7).

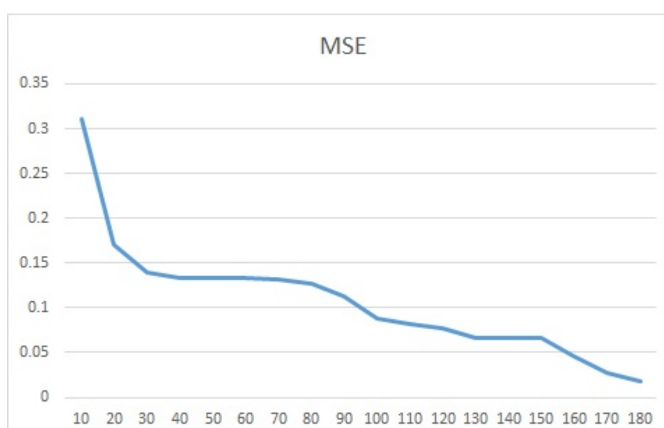

Fig. 7. Mean Square Error

TABLE I
COMPARISON OF PREVIOUS WORK AND CURRENT WORK.

Characteristics	Previous work	Current work
Training techniques	TensorFlow library on Python	Matlab code
Classification techniques	MLP and CNN	MLP
Classification accuracy	69% for 100 epochs	87% for 100 epochs
Database	MIT-BIH arrhythmia and kaggle.com	MIT-BIH arrhythmia
Classification of data	80% training 20% testing	80% training 20% testing

$$NMSE = |\frac{1}{2n}\Sigma_{i=1}^{n}(t-y)^2| \quad (6)$$

$$Accuracy = 1 - \sqrt{MSE} \quad (7)$$

For comparison, the first 100 epochs were selected from previous work and our work to check the NMSE and the accuracy. The NMSE of the previous work reaches 430 in the first epoch while it reaches 375 in our work as shown in Fig. 8. Then it decreases slightly until it reaches 83 for previous work and 20 for our work. Which means our work performs better and achieves minimum number of errors comparing to previous work and using the same simulation setup.

To compare the accuracy of previous work and our work, the first 100 epochs were taken as shown in Fig. 9. From the first epoch the accuracy reaches 54% in previous work while it reaches 40% in our work. After that, the accuracy increases slightly until it reaches 87% for our work and 69% of previous work after 100 epochs. Those results show that our work performed better in accuracy comparing to previous work for the first 100 epochs.

IV. CONCLUSION

IoT technology influence many researchers to find solutions for Homecare management systems. In this paper, we focused on homecare management system using cardiac arrhythmia classification into normal and arrhythmia. Signal filtering, feature extraction and classification are included in this model. The classification stage was applied using deep learning. Deep learning outperform machine learning in classification metrics due to the increasing number of hidden layers. To this end, classifying data using deep learning will help in improving the accuracy and reducing the number of errors for homecare management systems. Furthermore, our experiment results show that our model outperform the other researches in the cardiac arrhythmia classification purpose with higher accuracy and minimum number of errors. Future work will involve testing our method on new database and real patients to further improve the classification.

ACKNOWLEDGMENT

REFERENCES

[1] G. M. M. Shamim Hossain, "Cloud-assisted industrial internet of things (IIoT) - enabled framework for health monitoring," *The International Journal of Computer and Telecommunications Networking*, vol. 101, pp. 192–202, 2016.
[2] D. Ousaka, N. Sakano, M. Morita, T. Shuku, K. Sanou, S. Kasahara, and S. Oozawa, "A new approach to prevent critical cardiac accidents in athletes by real-time electrocardiographic tele-monitoring system: Initial trial in full marathon," *Journal of Cardiology Cases*, 2019.
[3] Z. Yang, Q. Zhou, L. Lei, K. Zheng, and W. Xiang, "An IoT cloud based wearable ecg monitoring system for smart healthcare," *Journal of Medical Systems*, vol. 40, no. 12, p. 1, Oct. 2016. [Online]. Available: http://dx.doi.org/10.1007/s10916-016-0644-9
[4] L. N. Mahdy, K. A. Ezzat, and Q. Tan, "Smart ECG holter monitoring system using smartphone," in *IEEE International Conference on Internet of Things and Intelligence System (IOTAIS)*. IEEE, 2018, pp. 80–84.
[5] J. N. Euan A Ashley, *Cardiology Explained*. Remedica, London, United Kingdom, 2004.
[6] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, May 2001.
[7] G. M. P. D. R.G. Mark, P.S. Schluter and D. Chernoff, "An annotated ECG database for evaluating arrhythmia detectors," in *Frontiers of Engineering in Health Care*. IEEE Computer Society Press, 1982, pp. 205–210.
[8] M. R. Moody GB, "The MIT-BIH arrhythmia database on CD-ROM and software for use with it," *Computers in Cardiology*, pp. 185–188, 1990.
[9] S. Savalia and V. Emamian, "Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks," *Bioengineering*, vol. 5, no. 2, p. 35, 2018.

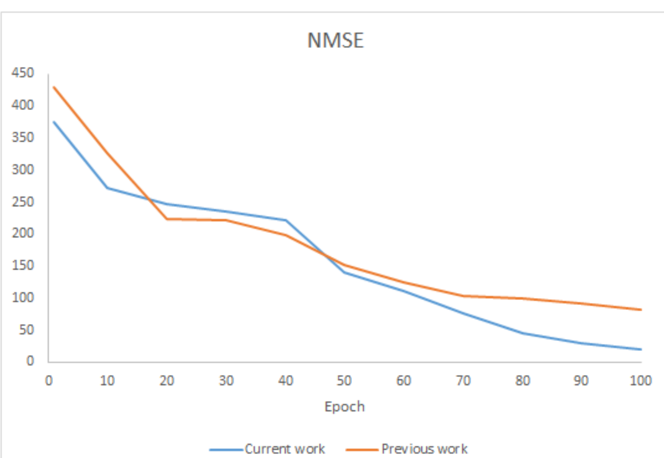

Fig. 8. NMSE

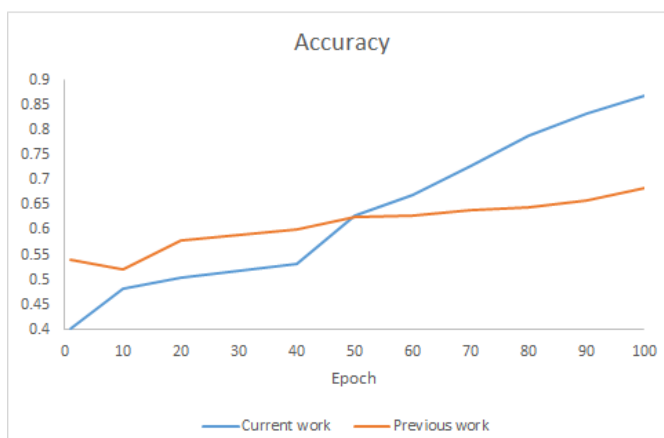

Fig. 9. Accuracy