Fog Computing based Heart Disease Prediction System using Deep Learning for Medical IoT

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***Abstract*—Internet of Things (IoT) is used in all areas because of the benefits it is offering. All most anything can be connected to the internet and data created by these devices can be analyzed to predict results. IoT is helpful in the medical field because it can connect the patients with the healthcare professionals, and the healthcare professionals can monitor their patients remotely and analyze their data and take necessary actions. Because of the huge amount of data in IoT systems, cloud services are utilized to store the data. But this is not a feasible option in medical IoT, because the predictions should be available as quickly as possible, since patients' lives are at risk. Therefore, edge-fog- cloud architecture is used. Fog nodes can be used to analyze data closer to the edge devices, resulting in much faster predictions and the cloud can be used for storage. This paper proposes a novel fog based architecture for medical IoT based on deep learning. Deep learning is used on the fog nodes to make accurate predictions. This study used data collected from heart patients to predict the heart disease to evaluate the system and yielded a good accuracy.**

Keywords— Medical IoT, Deep Learning, Fog Computing, Heart disease prediction

I. INTRODUCTION

Internet of Things (IoT) is now adopted in various fields and the devices connected to the internet has exceeded the population. When there are large number of devices, the data created by this devices are massive and to get valuable information this data should be processed and need to be stored. As a solution cloud computing is used. In the case of medical IoT crucial part is to provide real time data to the user.

Since data created by the medical field for one patient is considerably large specially when a patient is monitored continuously, hospitals need the help of the servers to store these data. [1] Once the data is stored there will be continuous queries to access the data as well as continuous updating of the data. This will be a problem to the network bandwidth.

Cloud computing is used with IoT because of the low cost, ability to store large amount of data and the maintenance cost. Therefore storing data in the cloud is a good option for the medical IoT field. However, there are also challenges with using cloud as servers. As mentioned earlier, because of the huge amount of data generated by the hospitals, when transmitting this data over the network it will be a burden to the network. At the same time when huge amount of data is transmitted over the network, there can be bit errors, trans- mission latency and packet droppings. These are proportional to the data transmitted. While a single bit error may not be a huge problem to some applications, medical IoT can not risk this, because it may lead to making incorrect decisions regarding the patient's health. [2]

As a solution to this, a new layer is introduced between the gateway and the cloud as the fog layer. [4] This layer can process the data and send processed information to the cloud rather than sending raw unprocessed data. This will help to reduce the burden on the network as well as the cloud. Fog computing can analyze data close to the devices and this will help in real time processing of the data and reduce the delays associated with it. Fog computing has all the required functions of the cloud to process the data. [3]

Fog computing architecture is a three layer model as shown in figure 1. The three layers are the IoT devices, fog layer and the cloud. Since the fog layer is very close to the IoT devices it has the location awareness of the devices which is needed to support the mobility. [6]

After the analyzing step is brought closer to the edge devices, next problem is analyzing the data. Deep Learning (DL) has shown good results in number of fields which has huge amount of data to process. [8] In IoT systems, machine learning and deep learning processes are used to analyze the data. [7] Deep learning has different variations such as Artificial Neural Networks (ANN) [9], Convolutional Neural Networks (CNN) [10], Recurrent Neural Networks (RNN) [11], Long short term memory networks [12], self organizing maps etc [13]. Each algorithm has its advantages and disadvan- tages for specific applications. Selecting a suitable algorithm for the specific study is the responsibility of the researcher and a vast research area.

Deep learning is a subset of Artificial Intelligence (AI). The objective of AI is to simulate human and develop programs to simulate the human brain. This include simulating the senses from eyes, ears, mouth and skin using cameras, microphones and robots. The subset deep learning is trying to make the neural connections that exist in the brain. These are used in the healthcare field to analyze and interpret signals and images and for clinical diagnosis. [14]

The challenge of using deep learning in Fog computing is

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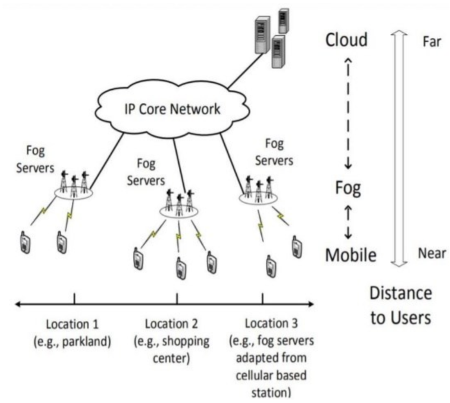

Fig. 1. Fog Architecture [5]

that fog devices have limited resources to perform analysis and therefore the algorithms used in usual healthcare applications and IoT applications may not be suitable for fog computing. In the medical diagnosis, detecting heart disease is a rather complex task, which requires the help of an experienced doctor. Sometimes people may not even know that they are suffering from a heart disease until they get a tachycardia or a stroke. [15] Using Deep learning to analyze the data from patients and predicting whether they have a heart disease or not will greatly help the patients.This study is focusing on finding the ability to use ANNs in fog computing for medical IoT to predict heart disease.

The remaining of the paper is organized as follows: The related work for this study is described in Section 2. Section 3 explains the artificial neural networks and in Section 4 the design of the system is explained. The results are reported, analyzed, and discussed in Section 5. Finally, the conclusion of the paper is drawn in Section 6.

II. RELATED WORK

Gia et. al [19] proposed a system to continuously monitor and analyze Electro Cardio Graphy (ECG) and to provide automatic notifications. This a a low cost system and consists of sensor nodes that are energy efficient and this system also consist of a fog layer. ECG, body temperature and, respiration rates are taken by sensor nodes and these data are transmitted to a smart gateway to be accessed by caregivers. A microcontroller, an nRF block and bio sensors are the components of the sensor node. Orange Pi one is used as the gateway to the system. Python application in Orange Pi One collects data from sensors and stored the data in a database and the cloud. Fog layer is used for data processing using algorithms. This systems consumes more energy, when transmitting over large distances.

He et al. [20] implemented a system called FogCepCare which is a fog cloud computing complex event processing hierarchy. This system tries to reduce the response time and the wastage of resources. They proposed optimization techniques for the system which included a partitioning and clustering approach and to optimize fog and cloud computing. It included a communication and a policy for parallel processing. A control center, city service node, community service nodes are in this architecture. Cloud node was implemented using Intel Xeon, city node with Intel Core i7 CPU and the community node with Intel Core i5 CPU. This system was evaluated only for response time and not the accuracy.

A healthcare system with a wearable device to analyze the ECG signal locally and identify abnormal patterns was implemented by Akrivopoulos et al. [21]. This system also includes wearable devices, edge devices and cloud services. Intel Curie was used as the software for the wearable device and the K Nearest Neighbor (KNN) and Radial Basis Function (RBF) algorithms provided by the pattern matching engine provided by Intel Curie was used to analyze the ECG. Analyz- ing module consisted of two parts. The first one is the feature extraction module and the second one is the training and classification module. However, when there were large amount of requests to the cloud server consumed power increased and degraded the system performance.

IoT e-health application based on Software Defined Net- works (SDN) was proposed by Ali and Ghazal [22]. This sys- tem collects data through the mobile phone and find the health of the patient. They also find the type of heart attack. However, this system was not tested for cloud ad fog environments. Rajasekaran et al. [23] proposed an Internet of Medical Things (IoMT) system with mobile chargers which are autonomous to satisfy the energy requirements of the sensor nodes. Wireless energy transfer technology was used in this application. They try to distribute the energy from the charger to the nodes in such a way that nodes' operation is not hindered. They also used a simulated cloud environment but the system has a high latency to process the request from the patient.

HealthFog was designed to use deep learning in edge devices to analyze heart diseases by Tuli et al. [24]. They used Fog enabled cloud and FogBus to evaluate the system. Their system comprised of a body area network, gateway, FogBus modules, broker nodes, worker nodes and cloud center. Data filtering and preprocessing, resource manager, deep learning module, and ensembling module are the software components of the system. They used a Samsung Galaxy S7 as the gateway device, Dell XPS with Intel core i5 as the broker node, Raspberry Pi 3B+ as the worker node and Microsoft Azure as the cloud. Although their training accuracy was high, their test accuracy was low for this system.

A graph based attention module for healthcare was developed by Choi et al. [25]. This system can be used for electronic health records with hierarchical information. This system was used to predict heart attack and the results were compared with RNNs. But they used a small dataset and achieved a good accuracy compared to the RNNs. But the performance degrades for a large dataset.

Constant et al. [26] designed a system to perform data conditioning and filtering to generate analytics from wearable devices. In wearable Internet of Things, wearable devices are connected to the cloud. They designed a fog gateway using Raspberry Pi and Intel Edison. Fog gateway will perform the data conditioning, filtering and selective transfer to the cloud. They optimized their system in terms of execution time and energy consumption.

Azimi et al. [27] designed a system with hierarchical computing architecture to allocate heavy tasks to the cloud. They deployed CNNs to a real time health monitoring system. They evaluated their system by using ECG data. ESP 8266 is used as the sensor node and the edge device is an Ubuntu Linux machine. They compared the performance when the analysis of ECG data was directly done on the cloud, to the analysis done on the edge device.

Mahmud et al. [28] proposed an IoT healthcare solution based on fog architecture. They used iFogSim simulator to compare the fog based architecture with the general cloud ar- chitecture for interoperability in the healthcare solutions. They evaluated their system on latency and power consumption.

III. BACKGROUND

A. ANN

Typically, ANNs can be used to estimate nonlinear com- plex functions. It can have multiple hidden layers, multiple inputs, and outputs. Figure 2 shows a ANN with K inputs, 1 hidden layer, and 2 output. The number of hidden layers can be adjusted according to the requirements of the problem being solved. Each input is multiplied by a weight. Initially, these weights are chosen randomly. These terms are summed together with a bias. These results are the inputs to the activa- tion function. Common activation functions are a hyperbolic tangent or a sigmoid function. The function is denoted by g in Figures 2 and 3. x, w and θ are inputs, weights and bias, respectively. n is the input to the activation function where,

$$n = \sum_{j=1}^{K} w_{ji} x_j + \theta_i \qquad (1)$$

Subscripts i and j denote the number of the layer. Levenberg-Marquardt algorithm was used as the training func- tion of the ANN [16].

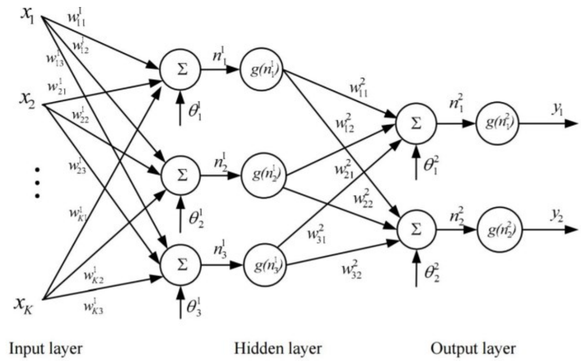

Fig. 2. ANN with 1 hidden layer [16]

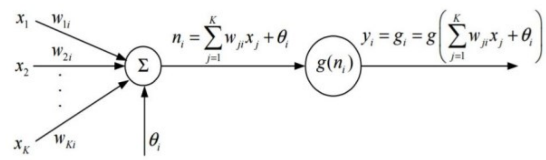

Fig. 3. A single node in ANN [16]

The output of node i can be written as

$$y_i = g\left(\sum_{j=1}^{K} w_{ji} x_j + \theta_i\right) \qquad (2)$$

In Figure 3 a single node in the ANN is shown separately [16]. Previous studies in [17], [16], used a multilayer feed-forward back propagation ANN with N input neurons, and 1 hidden layer and 2 output neurons to measure Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP). Yuri et al. used time domain features extracted from PPG as the inputs to an ANN [18], while Xing et al. used frequency domain features [17].

B. MQTT

Message Queuing Telemetry Transport (MQTT) is most commonly used protocol in IoT. It is a light weight messaging protocol and uses subscriber/publisher model to exchange data between server and the clients. This is ideal for IoT because of its small size, low power consumption, ease of implementation and use of minimize data packets.

The MQTT is based on a client server model. Server is responsible for handling client's requests and transmitting data between clients and the server. MQTT server is called a broker and the clients are devices. When a device needs to send data to the broker, the operation is publish and when a client is requesting data from the broker, the client is subscribing. If there are multiple data then publish/subscribe should be done for a topic. [29]

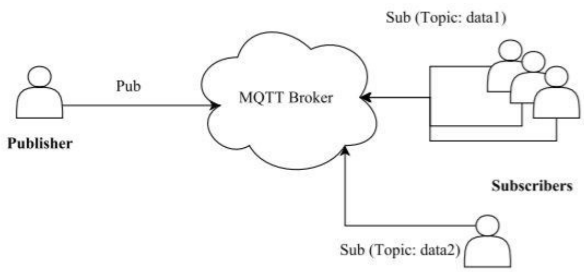

Fig. 4. The data communication over MQTT protocol **[29]**

IV. SYSTEM DESIGN

In this paper a IoT fog based system is proposed to detect the heart disease of the patients. This can be implemented inside a hospital without incurring a large cost. There are three levels in this system and they are edge-fog and cloud. The entire system is shown in Figure 5.

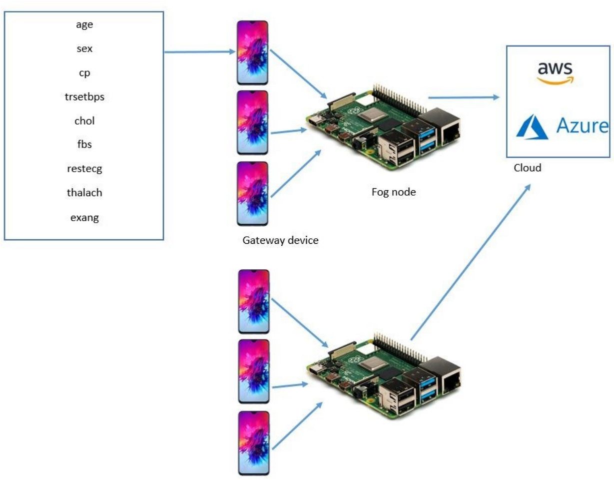

Fig. 5. Overview of the system

A. System Architecture

In this proposed system, edge devices are mobile phones which is used to enter the data into the system. Second layer is the fog layer which in this case is implemented using a Raspberry Pi. The data at the final stage will be sent to the cloud for storing. Each fog node can be used by ten edge devices. This will reduce the amount of fog devices inside the hospital premises. Since the fog device only need a power supply and access to the network, the nodes can be placed according to the areas where patients are diagnosed.

Initially, by using existing data, ANN is trained and the deep learning model is created. Created deep learning model is stored in each fog node. When the user enter the data for a new patient, the fog node will analyse the new entry and using the deep learning model, predict the result. Then at the final stage the result will be stored in the cloud.

To transfer data between edge device and fog node and between fog node and the cloud, the MQTT protocol is used. The fog device will act as the MQTT broker and the edge device will be the publisher and the cloud is the subscriber. Since MQTT is a light weight protocol, it can be easily used here without burdening the network.

B. System process

The flow chart for the system is shown in Figures 6 and 7. In the Figure 6, the DL process is shown. The model is trained on the training data first in one of the fog nodes and to validate the model, test data is used. After reaching the preferable accuracy, the DL model is stored on all the fog nodes.

Once that is done, the system is ready to accept data from the user, as shown in Figure 7. The user will enter the predefined data to a form in the edge device. The edge device will send the data to the closest fog node using the MQTT protocol. The fog node will use the DL model stored in the device to predict the heart disease. Finally, the result will be shown to the user by sending information to the edge device as well as stored in the cloud.

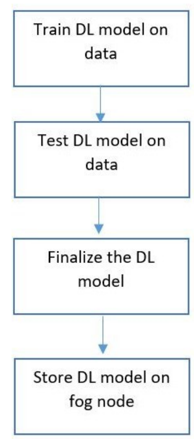

Fig. 6. Process of creating the DL model

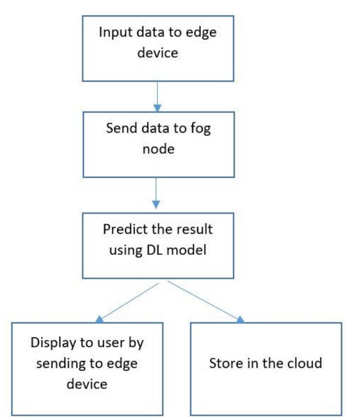

Fig. 7. Process of predicting the result

C. Specifications of the system

In this system an android phone is used as the edge device and the Raspberry Pi is used as the fog node. Their specifications are as follows.

Edge device noitemsep

- OS- Android 10, One UI 2.5
- Chipset- Exynos 9611 (10nm)
- CPU- Octa core (4x2.3 GHz Cortex-A73 and 4x1.7 GHz Cortex A53)
- GPU- Mali-G72 MP3
- Internal memory- 64GB 6GB RAM, 128GB 6GB RAM, 128GB 8GB RAM UFS 2.1
- WLAN- Wi-Fi 802.11 a/b/g/n/ac, dual-band, Wi-Fi Di- rect, hotspot
- Battery type- Li-Po 6000 mAh, non-removable Fog node noitemsep
- SoC: Broadcom BCM2837B0 quad-core A53 (ARMv8) 64-bit @ 1.4GHz
- GPU: Broadcom Videocore-IV
- RAM: 1GB LPDDR2 SDRAM
- Networking: Gigabit Ethernet (via USB channel), 2.4GHz and 5GHz 802.11b/g/n/ac Wi-Fi
- Bluetooth: Bluetooth 4.2, Bluetooth Low Energy (BLE)
- Storage: Micro-SD
- GPIO: 40-pin GPIO header, populated
- Ports: HDMI, 3.5mm analogue audio-video jack, 4x USB 2.0, Ethernet, Camera Serial Interface (CSI), Display Serial Interface (DSI)
- Dimensions: 82mm x 56mm x 19.5mm, 50g

V. Evaluation

To demonstrate the accuracy of the proposed system, an online dataset is used. The Cleavland dataset [30] contains data from heart patients and whether they have heart disease or not. From the attributes given in the dataset, 14 attributes are used for this system. They are explained below.

noitemsep

- age: age is given in years
- sex: 1 = male; 0 = female
- cp: chest pain type if type is 1: typical angina, 2: atypical angina, 3: non-anginal pain and 4: asymptomatic
- trestbps: resting blood pressure (in mm Hg measured when admitting to the hospital)
- chol: serum cholestoral in mg/dl
- fbs: (fasting blood sugar ¿ 120 mg/dl) (1 = true; 0 = false)
- restecg: resting electrocardiographic results if 0: normal, 1: having ST-T wave abnormality, 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
- 8thalach: maximum heart rate achieved
- exang: exercise induced angina (1 = yes; 0 = no)
- oldpeak = ST depression induced by exercise relative to rest
- slope: the slope of the peak exercise ST segment if 1: upsloping, 2: flat, 3: downsloping
- ca: number of major vessels (0-3) colored by flourosopy
- thal: 3 = normal; 6 = fixed defect; 7 = reversable defect
- num: diagnosis of heart disease if 0: not present, 1: present

Using this data, the DL model is trained. In the first step, the data is normalized using the standard scaler class in the SciKit learn package. Then the data is divided in to training set and test test randomly. ANN is created with two hidden layers and Relu as the activation function. For the output layer sigmoid function is used.

The accuracy and the loss of training is shown in Figures 8 and 9. The training accuracy of 0.86 is reached. A test accuracy of 0.86 is also reached and the confusion matrix is shown in Figure 10.

TABLE I
THE RESULTS OF ANN SHOWING TIME PER SAMPLE, TRAINING LOSS AND ACCURACY

Epoch	Time per sample	Loss	Accuracy
1	1s 3ms	0.7933	0.39
2	223us	0.7781	0.3776
3	229us	0.764	0.3859
4	206us	0.7511	0.4108
5	189us	0.7402	0.4315
6	201us	0.7286	0.4564
7	197us	0.7183	0.4855
8	213us	0.708	0.5145
9	198us	0.6978	0.5187
10	208us	0.6889	0.5353
11	223us	0.68	0.556
12	216us	0.6708	0.5602
13	200us	0.6621	0.5602
14	193us	0.6536	0.5768
15	204us	0.6445	0.6017
16	201us	0.6352	0.6183
17	277us	0.6265	0.6349
18	232us	0.618	0.6473
19	206us	0.6086	0.6722
20	215us	0.6003	0.6805
21	197us	0.5916	0.6929
22	188us	0.5835	0.7054
23	193us	0.5756	0.722
24	204us	0.56774	0.7344
25	192us	0.5595	0.7427
26	200us	0.5513	0.7469
27	197us	0.5534	0.7552
28	204us	0.5359	0.7593
29	212us	0.5277	0.7925
30	210us	0.5207	0.7925

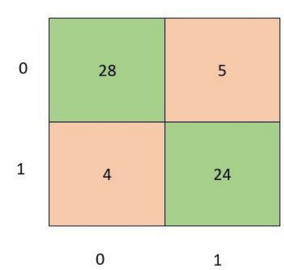

Fig. 10. Confusion matrix

A solution to this massive amount of data, cloud computing is used. But because of the network latency, analyzing the data on the cloud is not a feasible option. Therefore, fog computing, which analyzes data close to the edge devices, is used. In order to get higher accuracies, this study proposes a fog based medical IoT system with deep learning. This study achieves higher accuracy compared to other models and hence provide a novel architecture. Future works will include implementing and comparing other deep learning models on this proposed architecture.

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