FogDLearner: A Deep Learning-based Cardiac Health Diagnosis Framework using Fog Computing

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ABSTRACT

The application of the Internet of Things (IoT) and Artificial Intelligence (AI) in healthcare is an emerging domain. In Healthcare applications, relying on both IoT and AI requires paying attention to latency, responsiveness and management of data loads. Most of the healthcare applications are based on Cloud computing and use Cloud platforms such as Google Cloud and Microsoft Azure. With the increased adoption of IoT in various domains, the data generation rate and volume by IoT devices has tremendously increased, making the Cloud insufficient for latency sensitive healthcare applications. Fog computing, complementing the Cloud services, can be deployed close to the data source to better utilize distributed resources and meet the Quality of Service (QoS) requirements of healthcare application. In this paper, we propose a Fog-based cardiac health detection framework, called FogDLearner. FogDLearner utilizes distributed resources to diagnose cardiac health of a person without compromising QoS and accuracy. FogDLearner uses a deep learning based classifier to predict the cardiac health of the user. The performance of the proposed framework is evaluated on the PureEdgeSim simulator, in terms of resource utilization under overload and under-load scenarios, mobility support, and power consumption. The experimental results show the validity of proposed work for support of mobile applications.

CCS CONCEPTS

• Intelligent Heart Disease detection Systems; **• Fog-based healthcare systems**; **• Healthcare system Architecture**; **• Healthcare System** → Reliability;

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KEYWORDS

Fog computing, Deep learning, Smart healthcare, IoT, Cardiac disease detection

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1 INTRODUCTION

According to the World Health Organization (WHO), heart disease is a leading cause of death globally. In 2019, an estimated 17.9 million people died of heart diseases, about 32% of total global deaths [18]. Developing countries such as Pakistan witness a significant number of deaths due to late diagnosis of heart diseases. One of the reasons is that they are difficult to diagnose[7][19], as one does not realize the problem until an attack or stroke happens. Traditionally, symptoms observation and diagnosis are carried by an experienced medical professionals. These processes are unfortunately not always possible in practice due to shortage of doctors. Also, many countries still do not trust computer-based systems to detect heart related problems with required accuracy.

With recent advances in the Internet of Things (IoT) technologies, smart healthcare applications have received more attention in the research community. Thanks to smart healthcare systems, health parameters can be easily recorded using the IoT infrastructure. Not only does it save labour cost, but it also improves the diagnosis capability of the healthcare system [24]. IoT is an infrastructure that uses sensors, actuators, and communication technologies to make communication feasible between the real and the digital world. IoT devices used for healthcare systems generate excessive amounts of data [9]. Accessing data, processing it and triggering actions based on the user requirements requires significant resources while most IoT devices are resource limited (computation, storage, battery).

Existing smart healthcare applications are compute intensive. Where and how to process this collected data is a new area of research. Most of the smart healthcare applications are using the Cloud as their backbone, and upload a lot of data to the Cloud to be processed [5]. Huge volume of data generation and transmission from billions of IoT and mobile devices consumes significant bandwidth that can causes applications with tight delay requirement difficult to meet by Cloud as it is many hops away [25]. In smart healthcare systems, latency and response time are very important factors. Reacting fast enough to diseases like heart attacks can save many lives. Using Fog-based systems for healthcare can help to response in real time [9]. Fog nodes are placed near data sources. They can pre-process the raw data collected from the sensors, analyze and process it to reduce volume and size of data to be transmitted to the Cloud, reducing the demand for network resources and the burden on the Cloud [21]. Processing data at the proximity of users can get better latency, which means we can react to healthcare-related events in real time. Fog computing has emerged as a complementary technology to Cloud computing. It is considered as the best option for healthcare applications because of low latency, privacy, data security and its proximity to data sources [22].

Accuracy of diagnosis and fast response time are two equally important features in heart disease detection systems. For high accuracy of diagnosis of life critical diseases like heart disease, Deep Learning (DL) can be introduced running on Fog computing. DL is sub-field of Machine Learning. In recent years, it has outperformed traditional methods in many areas like cybersecurity, natural language processing, bio-informatics, robotics, and medical information processing[1]. DL uses multiple layers of artificial neural networks (ANN) to learn data and make intelligent decisions [2]. In deep learning, the word 'deep' refers to the depth of the layers. Among DL algorithms, recurrent neural network (RNN) have the deepest structure. RNNs are currently utilised to solve sequential learning challenges. Each layer in a RNN is interconnected and enables it to learn from the data over time. In incremental learning, the model continuously adjusts itself based on the inputs, and does not require to re-train the whole model but only learn from new samples. This approach is very helpful in learning complex data structures [14]. DL works effectively with time dependent, noisy, sparse, and heterogeneous healthcare data. Its end to end learning and the ability to process complex and multi-modal data is very advantageous in healthcare sector [15]. Heart diseases are a significant factor in most deaths. However, many other factors such as diabetes or high blood pressure make heart disease diagnosis more complex. Many techniques are used for cardiac health diagnosis such as Decision Trees (DT), Genetic algorithm (GA), Naive Bayes (NB) and so on. Among them, neural networks were considered the best way to diagnose heart diseases [16].

Previous works have performed training and testing of deep learning algorithms on Cloud platforms because the accuracy of the prediction depends on the amount of data. Unfortunately, sending data to the Cloud, processing it on Cloud and sending the results back [14], leads to unacceptable latency in many smart healthcare applications. We believe that combining deep learning and Fog computing could be an effective way to avoid these issues. This new direction of research takes advantage of Fog computing's ability to reduce response times while still obtaining good prediction.

Motivation of this work is to design a heart disease detection system which can respond in real time with reliable accuracy. The computing model for health care application must satisfy the following requirements: (1) Low latency, as fast response time can lead to reduced treatment cost and save patient lives, which require speedy data processing and transmission and also right places to process data, (2) Reduced usage of network resources, as not all the data need to be sent to the Cloud, (3) Accuracy and reliability of data because collected data determines the accuracy of diagnosis. Collected data can be noisier and less integral as it is collected from geographically distributed devices, (4) Accuracy of prediction as reliability of system depend on correct diagnosis (5) Capable of communicating with heterogeneous device because different devices may use different protocols for communication.

There is a need of standardized Fog based smart healthcare systems that can diagnose cardiac problem in real time with high accuracy.

This work proposes a deep learning based Fog enabled framework called FogDLearner for cardiac disease diagnosis that meets accuracy, fast response, privacy and low latency requirements of healthcare systems while considering energy consumption and mobility of devices in account. Evaluation of effectiveness of proposed work is done using PureEdgeSim [13].

The main contributions of this work are:

- FogDLearner, a Fog based framework for disease prediction that explores the trade-off between the accuracy of cardiac disease prediction and the quality of service parameters of Fog computing.
- A Fog based cardiac disease prediction case study and a deep learning model for cardiac disease prediction.
- We evaluate the proposed model on the PureEdgeSim simulator, in terms of latency, resource utilization and energy efficiency.

The rest of the paper is structured as follows. *Section. 2* presents related work in healthcare system. *Section. 3* describes the proposed framework and its modules. The implementation is presented in *Section. 4*. We provide and discuss the evaluation results in *section. 5*. Finally, *Section. 6* concludes and discusses future work.

2 RELATED WORK

Fog computing has appeared as a complementing technology to Cloud computing. It can efficiently process and manage data collected from a variety of sensors and IoT devices to the proximity of user. The benefits of Fog, together with the popularity of IoT-based Intelligent applications, the volume and rate of data generation from IoT devices, and the resource limitations of edge devices and latency sensitivity of healthcare domain, are collectively making the application of Fog in Healthcare a necessity. When applying Fog to healthcare, one must focus on improving the parameters (e.g accuracy, privacy, delay sensitivity, network usage) that ensure that the benefits of Fog computing in healthcare are effectively utilized. Negash et al.[17] proposed an IoT-based system for monitoring a person's Electrocardiogram (ECG) in real time. The architecture of the proposed system has three layers. The first layer consist of medical sensors, environmental sensors, and activity sensors. Medical sensors collect heart rate, respiration rate, body temperature, blood pressure, blood oxygen level, and ECG. The data is collected with a network of gateways. The data fusion and compression is done in Fog layer.

The Cloud layer is used for storage and analyzing the status of a person's health. The solution is designed to address the issues of

Table 1: Comparison of proposed work FogDLearner with existing healthcare models

Work	Fog	Mechanism	Heart disease	Power	Network usage	Execution Time	Mobility	Implementation
Tuan et al.[8]	✓		Monitoring	✓		✓		NA
Gia et al.[17]	✓		Monitoring	✓		✓		Prototype
Vijayakumar et al.[23]	✓	K-nearest nabour						Not mentioned
Asif et al.[3]	✓					✓		Not mentioned
Saha et al. [20]	✓					✓		Hyperledger composer
Tuli et al. [22]	✓	Ensemble Voting	Prediction	✓	✓	✓		FogBus
Devarajan et al. [6]	✓	J48Graft Decision tree		✓		✓		NA
Manocha et al. [12]	✓	K-mean Clustering and ANN				✓		Ubidots IoT platform
Awaisi et al. [4]	✓		Monitoring					iFogsim
FogDLearner (this work)	✓	Recurrent neural network	Detection	✓	✓	✓	✓	PureEdgeSim

high latency and bandwidth usage. A small scale test was implemented, showing a 48.5% reduction in network delay under high network load. However, the minimum latency is poor when the network load is not high. For monitoring and Control of mosquito-borne diseases, an intelligent Fog-based system is proposed in [23]. For the data collection, IoT and wearable sensors are used. The data analysis, clustering and data sharing is done at the Fog layer. The data used for the analysis include physiological conditions, symptoms of the disease, contextual information, whether or not that region is at risk, and mosquito density in the region. The Cloud layer is used for social network analysis to prevent extensive spread of mosquito-borne diseases. A machine learning algorithm classifies the user as infected or uninfected and identifies the type of disease. This work demonstrated 95.5% classification accuracy but did not consider important parameters of a standard system such as latency, QoS needs and energy consumption.

In another work[3], a Cloud-based heterogeneous Internet-of-Healthcare-Things communication framework is proposed. The framework is based on five layers: Perception layer, mist layer, Fog layer, Cloud layer and application layer. The goal of the work is to ensure high QoS, focusing on controlling end-to-end latency and packet drop rate using optimization of flow control and resource allocation. The evaluation was carried through a case study, which validates its suitability in the healthcare domain. However, it only focuses on data streaming and transmission rather than the processing and analysis of the data. Though Fog based healthcare systems have demonstrated their value in terms of response time and low latency, architectures of this type also increase the challenges in terms of privacy and security. Privacy and security concerns need to be carefully addressed to take full advantage of Fog based frameworks. Saha et al.[20] worked on privacy preservation of medical records. At the Fog layer, they used a data aggregator that reduces the burden on the network. To ensure confidentiality and reliability of the records, Elliptic cryptography and Consensus algorithms were used. Their results suggested that using a data aggregator at Fog layer can minimize response time to some extent, and that Elliptic cryptography can preserve the privacy.

Another Fog-based energy-efficient healthcare system proposed in [6], that monitors diabetic patients' nutritional intake and physical activity to manage blood glucose levels. For accurate prediction of blood glucose risk level they used J48Graft decision tree. The evaluation was done by running a case study on smartphones. The results showed that in the case of continuous detection and judgement, its performance is better in the Fog than the Cloud. As it was a case study implemented using mobile phone, it does require larger scale experiments on larger scale in cariety of scenarios. Shreshth et al. [22] proposed an ensemble learning based heart disease prediction system. However, they have not considered the mobility of devices in their experiments, while these have an impact on the execution of tasks. An IoT and Fog based e-health framework has been proposed by Manocha et al.[12]. This framework determines the physical fitness of sedentary people. A wide variety of devices such as actuators, RFID tags, mobile phones, and smart sensors are used to sense data. The datasets of Health, Physical posture, Behavior and Environment were combined for the analysis. For the latency sensitivity of their system, the pre-processing was done on the Fog layer and the analysis in the Cloud. They used ANN and the experimental results showed 94.51% accuracy for the prediction of health abnormalities. Other performance criteria such as energy usage and network utilization were not evaluated in this study.

A comparison of the proposed frameworks is presented in Table 1. However, in the application scenario of diagnosing cardiac disease, there is a need to process data close to the body, with high prediction accuracy and low energy consumption. Therefore, a more detailed evaluation of Fog-based healthcare systems is necessary in this case.

3 FOGDLEARNER: PROPOSED FRAMEWORK

This section describes the architecture of our framework , including the flow of data between its components. The proposed model can effectively diagnose a patient's cardiac health status and manage its data in real time. It consists of three layers: the IoT layer, the Fog Layer, and the Cloud Layer. Figure 1 presents a detailed view of the components.

3.1 IoT Layer

This layer collects two types of data and send the data to the gateway device: Physiological data (PD) and Electronic Medical Records (EMR). For the collection of physiological data, medical, environment and activity sensors are used. Heart disease parameters are captured via the following sensors: EEG, EMG, ECG, Heart rate, body temperature, Oxygen saturation, glucose level, respiration rate and blood level.

Gateway node The gateway device collects data from sensors and EMRs and sends that data to the Fog broker or to worker nodes. This role can be played by mobile phones, tablets or laptops.

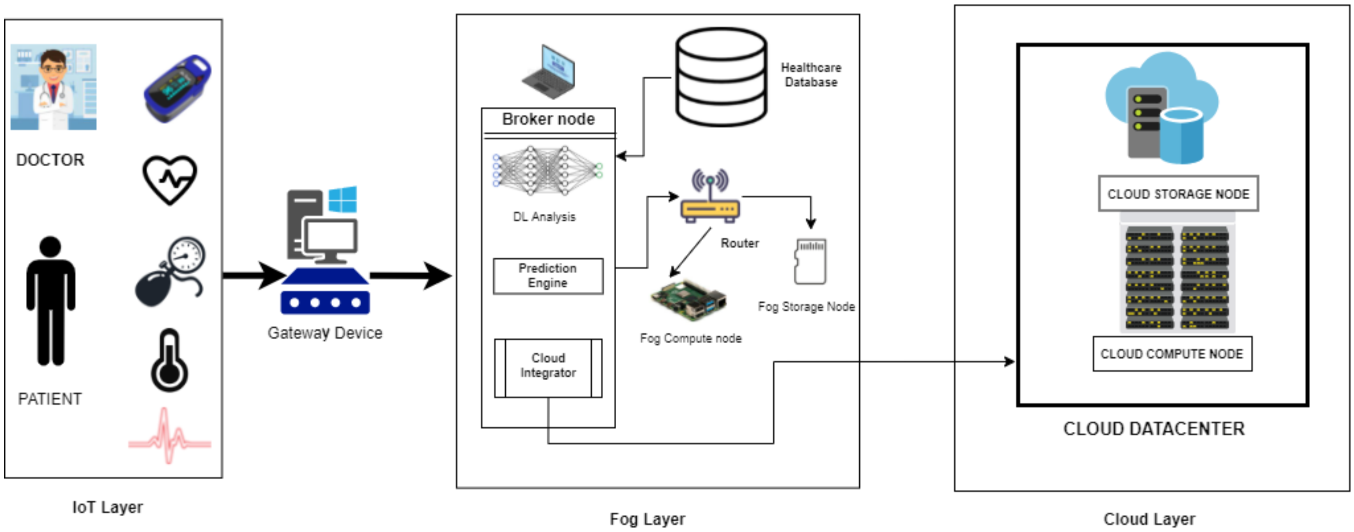


Figure 1: FogDLearner framework.

3.2 Fog Layer

This layer consists of the Broker node, the Fog compute node and the Fog Storage node.

- **Broker Node:** The broker node receives tasks and data from gateway devices and based on the availability index (AI) of the Fog compute nodes and the Fog Storage nodes, it assigns tasks to Fog compute nodes. The broker and Fog nodes work in a master-slave manner. The broker node is made of two parts: the Prediction Engine and the Cloud Integrator.
  Prediction Engine: Upon receiving the data and a task from the gateway node, the data is sent through the prediction engine, which analyse the work load for the predicting the data using Deep learning. If the Availability index is greater than the threshold limit, the data is sent to the Cloud integrator for further processing, or to the router (see below) for further processing.
  Cloud Integrator: If the data comes to the Cloud Integrator from the prediction engine, it transmits the data to the Cloud data center for further prediction. It acts as a communication device between the Cloud data center and the Fog layer.
  Router: It is the intermediate device responsible for the transmission of the data from broker node to Fog compute node and Fog storage node.
  Fog Compute Node: This node contains the trained RNN model. Upon receiving the data from the router, the trained model predicts the heart condition of the user. As the fog nodes does not require high computational power and storage, so using a Embedded system like Raspberry pi will reducing energy consumption and also be reducing the cost of the entire infrastructure.
  Fog Storage Node: It is responsible for storing data in the Fog layer.

3.3 Cloud Layer

When the Availability index is larger than the threshold, then the data is sent to this layer by the Cloud integrator. This layer consist of two parts: Cloud Compute node and Cloud Storage Node.
Cloud Compute Node: This node is equivalent to the Fog Compute Node in the Fog layer. It also has the same trained RNN model used for prediction.
Cloud Storage Node: This node is equivalent to the Fog Storage used for storing the data in the Cloud layer.

In Algorithm 1, we provide pseudo-code describing the step-by-step operation of FogDLearner. First, Physiological Data (Pd) and Electronic Medical Records (EMR) are received from the users via sensors in the IoT layer and sent to a gateway device. These data are collected and sent to the Broker Node in the Fog Layer in the Gateway device. Depending on the availability index (Ai), the broker node sends the data to the DL module in the Cloud Layer or Fog Workers. There is no loop in the Pseudo Code. Also, there is no loop inside of the if-else condition either. Thus, the time complexity is O(1).

4 PERFORMANCE EVALUATION

To demonstrate and assess the applicability of the proposed solution, we rely on a case study and deploy our solution on PureEdgeSim. The experiment contains two main parts. Experiment I evaluates our ML model for heart disease using azure ML and experiment II evaluates the performance of the proposed architecture in terms of execution time, network usage, energy consumption, and resource utilization using the PureEdgeSim simulator.

4.1 Case Study: Cardiac disease prediction

As previously mentioned, we focus on Cardiac disease detection in this paper as a case study. In [22], the Data are used to predict whether the person will have disease or not, it is a precautionary action, whereas in FogDLearner, it is a curative action to detect the

Algorithm 1 The FogDLearner Operating Mechanism

Input: $\mathbf{P_d}$ **and EMR**
Output: $\mathbf{H_D}$ **Positive** or $\mathbf{H_D}$ **Negative**
Begin
  IoT Layer:
   Receive $(\mathbf{P_d} \oplus EMR) \longrightarrow$ Gateway
   Gateway Device:
    $\sum (\mathbf{P_d} \oplus EMR) \longrightarrow$ Broker Node
  Fog Layer:
    If $\mathrm{A_i} < \tau$:
      $(\mathbf{P_d} \oplus EMR) \longrightarrow$ Fog Workers for **DL**
      Return $\mathbf{H_D}$ *Positive or* $\mathbf{H_D}$ *Negative*
    else:
      $(\mathbf{P_d} \oplus EMR) \longrightarrow$ Cloud Layer for **DL**
      Return $\mathbf{H_D}$ *Positive or* $\mathbf{H_D}$ *Negative*
End

category of heart disease happened to the paitent on the basis of his EMR and PD.

4.2 Dataset

For the experiment, we considered the Heart patient dataset from the UCL Machine Learning Repository [11], which was created by Andras Janosi (M.D.) from the Gottsegen Hungarian Institute of Cardiology. Each record of the dataset has 14 attributes. The presence of a disease is represented by a binary variable (1 meaning the patient has a heart disease and 0 otherwise). The attributes from the dataset are shown in Table 2. A sample record taken from 10 patients is provided in Table 3.

4.3 Two-class Recurrent Neural Network model

A two-class Recurrent neural network is employed for our case study, to determine whether a user has a heart disease or not.

It is divided into two subsets, training and testing set. The dataset used for training prediction model is 70% of the total data set, 30% is used for validation. The model is then validated using cross validation. The lists of parameters that employed in the prediction model are given in Table 4.

4.4 Simulation in PureEdgeSim

The simulated environment comprises of a Cloud, four Fog data centers and four Fog devices. Two of the Fog devices are considered mobile and the other two are fixed. Sensors are connected to each device and they are continuously generating data. Fog servers are working in master-slave mode: one Fog node acts as Fog broker and the other three are workers. They have performance differences. The Cloud is handling data overload situations. The parameters specific to mobile devices and fixed devices are given in Table 5.

Execution Time: Execution time of the task is calculated as:

$$T^{total} = T^{tran} \oplus T^{exe} \oplus T^{rec} \oplus T^{mig} \tag{1}$$

where T^{tran} ,T^{exe},T^{rec} and T^{mig} denote the transmission time from sensor to Fog server, the execution time at the Fog server, the time spent in returning results from Fog server to Fog device and, the migration time between Fog layers, respectively.

Energy Consumption: It is calculated as the sum of transmission energy, idle energy and load energy utilization.

$$E^{total} = E^{trans} \oplus E^{idl} \oplus E^{util} \tag{2}$$

$$E^{trans} = \frac{Data\ transmission}{Bandwidth} \times Ptransmission \tag{3}$$

$$E^{idl} = \frac{TaskWorkload}{Task\ processing\ speed} \times Pidle \tag{4}$$

$$E^{util} = \frac{TaskWorkload}{Task\ processing\ speed} \times Pend \tag{5}$$

Where as E^{trans} denotes transmission energy from sensor to Fog layer, E^{idl} represents idle energy of all device, E^{util} represents the load energy utilisation.

5 EXPERIMENT RESULTS

5.1 Training and Testing Accuracy of Heart Disease Predicting Model

Neural networks have demonstrated their ability to predicting cardiac diseases already. Two class neural networks guarantee a good trade-off between training time and performance. The Receiver Operating Characteristic (ROC) curve of the training and testing sets are shown in Figure 2. The confusion matrix and precision measurement parameters are also given in Figure 3, and Table 6 at threshold value 0.5. 90.07% sensitivity indicats a good sensitivity of classifier to predict positive instances. 78% Specificity of classifier indicates 78 percent of all patients that didn't have heart disease are predicted correctly.

The closer the Area Under Curve (AUC) of ROC is to 1, the better the recognition ability of the model. The AUC of 0.948 suggests a good performance. It has a lot of room for improvements, which can be done by relying on more data.

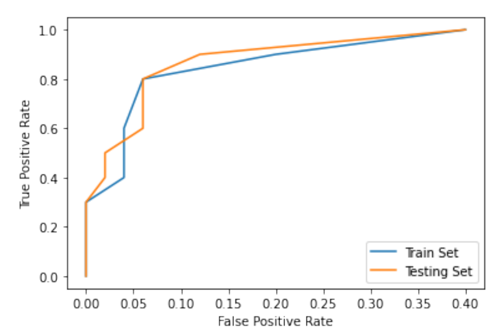


Figure 2: Training and testing set ROC curve

5.2 Performance of Proposed Architecture in PureEdgeSim

The performance of the proposed architecture is evaluated using the PureEdgeSim simulation tool.

Table 2: Heart dataset attributes

Sr#	Attribute	Description	Possible values
1	age	Age of person in years	*Natural number*
2	sex		*1→ male, 0→female*
3	cp	Chest pain	*1→typical angina, 2→atypical, 3→non anginal pain, 4→asymptomatic*
4	trestbps	Resting blood pressure	*90-200*
5	chol	Serum cholesterol in mg/dl	*125-256*
6	fbs	when fasting blood sugar >120 mg/dl	*1→ no, 0→yes*
7	restecg	This attribute represents resting electro-cardiographic results	*0→normal, 1→presence of ST-T wave abnormalities (T-wave inversion and/or ST elevation or depression > 0.05 mV), 2→possibility of left ventricular hypertrophy.*
8	thalach	Maximum heart rate	*71-202*
9	exang	Patient suffer from exercise induced angina	*1→ yes, 0→no*
10	oldpeak	ST depression induced by exercise relative to rest	*0-7*
11	slope	The slope of the peak exercise AST segment	*1→ upsloping, 2→flat, 3→downsloping*
12	ca	number of major vessel colored by flourosopy	*0-3*
13	thal	A blood disorder called thalassemia	*3→ normal, 6→fixed defect, 7→reversible defect*
14	Output	Diagnosis of heart disease	*1→ larger than 50% diameter narrowing, 0→ less than 50% diameter narrowing*

Table 3: Sample record from dataset

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
57	1	0	140	192	0	1	148	0	0.4	1	0	1	1
61	0	0	130	330	0	0	169	0	0	2	0	2	0
58	1	2	112	230	0	0	165	0	2.5	1	1	3	0
50	1	0	150	243	0	0	128	0	2.6	1	0	3	0
44	1	0	112	290	0	0	153	0	0	2	1	2	0

Table 4: Parameters of neural network employed in prediction model.

Parameters in neural network	Value
Number of hidden nodes	100
Learning rate	0.1
Number of learning iterations	100
Initial learning rate	0.1
Type of normalizer	Min-Max normalizer

We considered the execution delay, resource utilization, power consumption and network usage as evaluation criteria. We have evaluated the performance of FogDlearner in terms of execution time and used equation 1 to measure its value in milliseconds (ms). Figure 4 shows the execution time for different workloads in terms of number of devices. We observe a linear scaling of the execution time both for Fog and the Cloud, simply shifted up to higher values in the case of the Cloud. There is a visible difference in execution times. Execution time of task on cloud is very low because of high availability of resources but sending data to the Cloud increase total execution time calculated using equation 1. Since this is a simulation based experiment, implementing it in real environment can increase this difference. Because, in real experiment environments,

Table 5: Parameters of moving and fixed devices.

Parameters	Mobile device value	Fixed device value
Moving speed(m/s)	1.4	0
MinPauseDuration	100	0
MaxPauseDuration	400	0
BatteryCapacity(Wh)	18.75	False
IdleConsumption(Wh/s)	0.0001	1.6
MaxConsumption(Wh/s)	0.0011	5.0
Million instructions per second	25000	25000

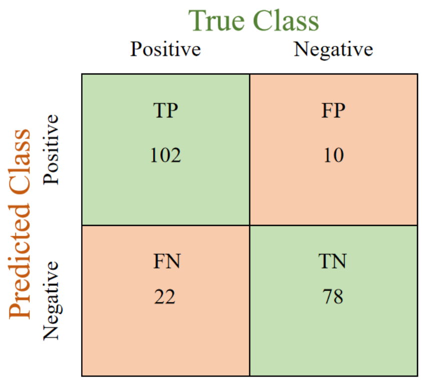


Figure 3: Confusion Matrix.

some other parameters that affect the total execution time, such as internet bandwidth [10], come into play.

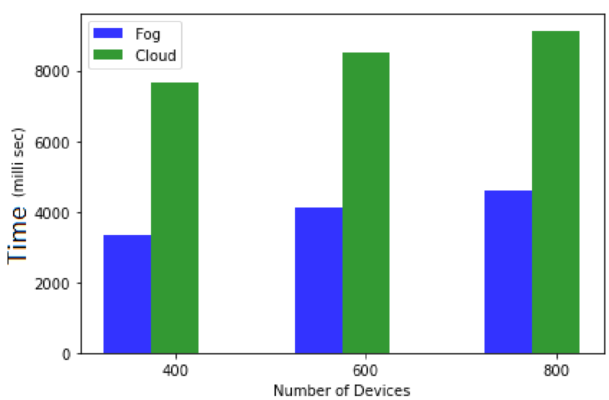


Figure 4: Comparison of execution time.

Figure 5 compares the network usage of FogDlearner with a Cloud-only approach. Again, as for the execution time, we observe a linear scaling both for the Fog and Cloud approaches, as a function of the number of devices.

As FogDlearner processes data close to the user, the data is only sent to the Cloud for processing in case Fog nodes get overloaded. This reduces the network usage in FogDLearner, which is desirable in today's growing IoT environment.

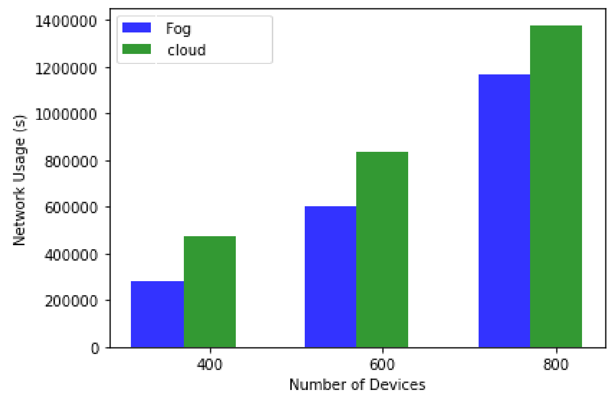


Figure 5: Comparison of network usage.

We also evaluate FogDLearner in terms of energy usage. We rely on Equation 2 to measure the energy consumption in watt-hour (wh). Figure 6 shows energy consumption as we increase the number of devices using the application. Here, we observe a clear linear scaling as for the previous results. As the number of devices increases, the amount of energy consumed in Cloud and Fog increases linearly. Figures 7a and 7b compare the resource utilization

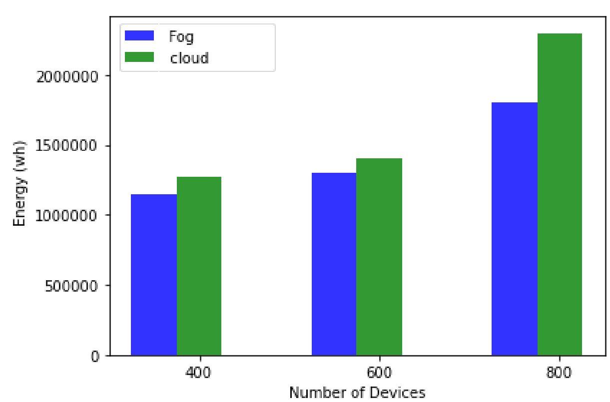
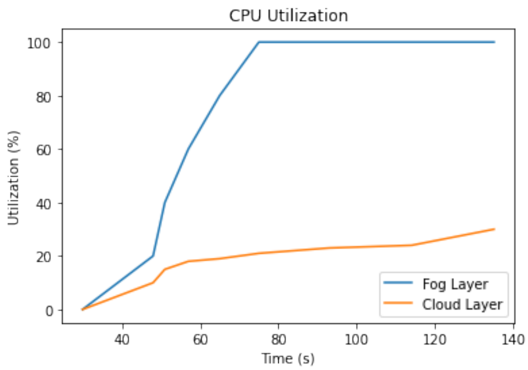
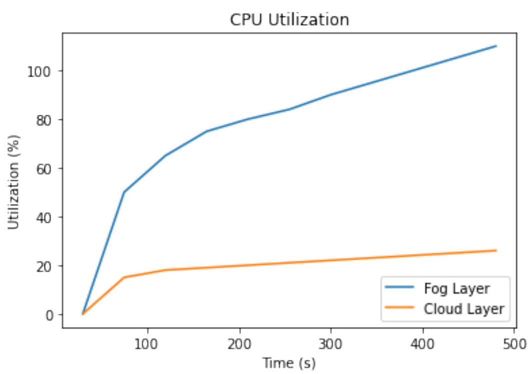


Figure 6: Comparison of energy consumption

in Fog using FogDLearner and Cloud-only, under under-loaded and over-loaded scenarios. We change the load of a scenario by adjusting (decreasing or increasing) the number of tasks. We observe that in the over-loaded scenario (Figures 7a), the CPU utilisation reaches 100% relatively fast in the case of the Fog approach, while the Cloud scales better. In the under-loaded scenario, we observe that the Fog reaches high CPU utilisation faster than the Cloud, as expected.



(a)



(b)

Figure 7: Comparison of CPU utilization in underload (a) and overload (b)

In summary, our experimental results show that FogDLearner shows good performance with respect to delay, energy consumption and network usage, while maintaining a good accuracy of diagnosis of heart disease.

In comparison to [18], where the ensemble learning is suggested for accuracy, FogDlearner show low latency. As the ensemble based deep learning method requires to train a large number of neural networks, so this require much more bandwidth and energy compare to a RNN. If energy and network bandwidth constraints exist, ensemble learning is not recommended for latency critical applications. In voting based ensemble learning test accuracy decreases with increase in number of nodes because each node gets a smaller subset of training data and hence is unable to generalize the model.

6 CONCLUSIONS AND FUTURE WORK

In this work, we proposed a framework called FogDLearner, and conducted experiments using a use case related to cardiac health prediction. We compared the adequacy and performance of FogDLearner

Table 6: Performance Metrics

Parameters	Values
Accuracy	84.91%
Precision	82.26%
Sensitivity	91.07%
F-Score	86.44%
Threshold	0.5
AUC	94.9%
Specificity	78%
Negative Predictive Value	88.64%
False Discovery Rate	17.74%
Matthew's Correlation Coefficient	69.98%

using the PureEdgesim simulator. We compared our approach against a Cloud-only one. We also confirmed the adequacy of neural networks for accurate prediction of cardiac disease.

Most of the sensors and edge devices used to monitor and collect data for healthcare systems are resource constrained. Conservation of energy of these devices is a big challenge on Fog. More intelligent algorithms for offloading tasks from low to more powerful devices are required.

In future, FogDLearner should incorporate dynamic scalability to analyze execution time scale with number of devices.

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