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Grid-Based Prediction model for Coronary Heart Disease: Using Data Generated from the IoT-based Health Monitoring Systems

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Abstract
Internet applications are now closely associated with human life and hence, have become inevitable in human daily activities. This has resulted in the deployment of various types of sensors and computing devices in huge numbers. One of such is the network of objects which are interconnected to create and share data, called the Internet of Things (IoT). Amongst the applications enabled by the Internet of Things, the continuous health monitoring system (HMS) is a particularly important one. Therefore, this study was carried out to design architecture on fog network, that acquires data from IoT-based Health monitoring systems using Radio Frequency Identification-RFID, and develop a prediction model that predicts coronary artery disease using Artificial Neural Network. The existing heart disease datasets from the UCI Machine Learning Repository was used. In our result, the confusion matrix, in the order of (True Positive, False Positive, True Negative, False Negative) gives 41%, 8%, 40.3%, 10.6% respectively. Equal Error Rate: 0.1867, Accuracy: 0.8132, Sensitivity: 0.7939, and Precision: 0.8362. Finally, Receive Operative Characteristic (ROC) gives 0.8034. Having fully explored and implemented this model, the performance of our model was examined and compared with another work and we found out that our model out-performed the model in terms of accuracy and precision.

Keywords: *Internet of Thing, Coronary Artery Disease, Radio Frequency Identification, Health monitoring System*

1. Introduction

Technology today, is being refined continuously to seamlessly integrate itself into the routines of the human world. The cloud has helped in providing the platform to accommodate the operations of various forms of applications which can assist in simplifying the complicated processes in various domains, that is, automation. This has resulted in the deployment of various types of sensors, computing devices in huge numbers. One of such is the network of objects which are interconnected to create and share data called the Internet of Things (IoT).

The Internet of Things (IoT) refers to the new generation of the Internet that contains trillions of nodes representing various objects from the smallest common sensor devices and handhelds to large web servers and supercomputer clusters [1]. IoT increases accuracy and efficiency and also improves economic benefits [2]. Therefore, its benefit cannot be overemphasized. Despite the broad utilization of cloud computing, some applications e.g. IoT-based applications still cannot fully benefit from it due to its inherent challenges such as high latency, location-awareness, etc. Since data centers of clouds are located near the core network, those applications and services will suffer unacceptable round-trip latency when data are transmitted from/to the end devices to/from the cloud data center through multiple gateways. Hence, fog computing has emerged as a promising infrastructure to provide elastic resources at the edge of the network.

It is quite essential to note that the proximity in terms of distance of fog computing to end users has made it have an edge over the cloud. Data generated by environmental sensors and some other IoT devices are recorded at time intervals that need to be mined in real-time, in a way that

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takes into consideration the dynamic natures of the real-world changes that are being measured.

This is not easy to achieve in cloud computing hence, there is a need for fog computing i.e. computing infrastructure that is dedicated to IoT.

A IoT in Healthcare

Amongst the applications enabled by the Internet of Things (IoT), the continuous health monitoring system is a particularly important one. The healthcare industry amongst others is information-rich and can be difficult to handle traditionally. Such vast data are very essential in data analytics for the extraction of valuable information and generate relationships amongst the data attributes. For example, wearable sensor devices are used for suggesting physiological exercises and food habits by a two-three day period of continuous physiological monitoring of patients, during which wearable sensors would continuously observe and store the patient's health data into a data store for diagnosis and future investigative purposes.

Thus, sensor data is most often used for taking appropriate action for the patient's health and treatment recommendation, lifestyle choices, and early diagnosis that are essential in improving the quality of patient health. [3]. However, there exist some challenges facing IoT based Health Monitoring Systems in healthcare, some of which were explained in [4]. These include storage, integration, interpretation, and managing of the huge mass of incoming data. Others include data accuracy and security and real-time access to data.

There is, therefore, a need for an architecture that can collect data from various heterogeneous IoT-based Remote Health Monitoring Systems i.e an architecture that offers a computing and data management infrastructure for supporting decentralized and parallel data analysis, from different locations, integrate and store data to apply the algorithm that is capable of dividing the computational workload among multiple nodes while ensuring data security, low latency, and data accuracy. Our model met the above requirements by taking advantage of fog computing - a computing infrastructure that is situated between the edge of the cloud and IoT. Fog extends applications, data, services, and computing power network of the cloud computing paradigm from the core to the edge of the cloud thereby bringing it closer to IoT devices to enables the processing of IoT generated data near data sources i.e. IoT devices [5]. See figure 1. This enables (1) a significant reduction in the volume of data that must be moved between IoT devices and the Cloud, (2) real-time and online analytic even when connectivity is poor or lost with the Cloud [6].

Considering the importance of life, and individual's struggles to live a healthy life, one would conclude that no amount of money spent on sustaining one's health is too much. But the fact is that not all individuals can afford to pay the expensive bills. However, for patients whose health conditions are not considered bad enough for admission, the use of some conventional hospital equipment especially the ones used in monitoring patients over a period would considerably be a waste of time. Also, taking the readings of some of this equipment used in carrying out hospital tests further requires the clinician to manually interpret it, which at times involves some calculations.
This calls for manual paper documentation which could be lost, damaged, and useless for knowledge discovery purpose where Big Data is required.

Finally, data generated by IoT devices are recorded at time intervals that need to be mined in a way that takes into consideration the dynamic natures of the real-world changes that are being measured. Therefore, there is a tremendous need for a data analysis system that can mine massive and continuous stream of real-world data. Therefore, in this study, a grid-based architecture was designed to mitigate the technical challenges facing the IoT-based Health Monitoring Systems such as data accuracy and security, real-timeliness, system integration, and data intensiveness by leveraging on fog computing to develop a prediction model for coronary artery disease using Artificial Neural Network

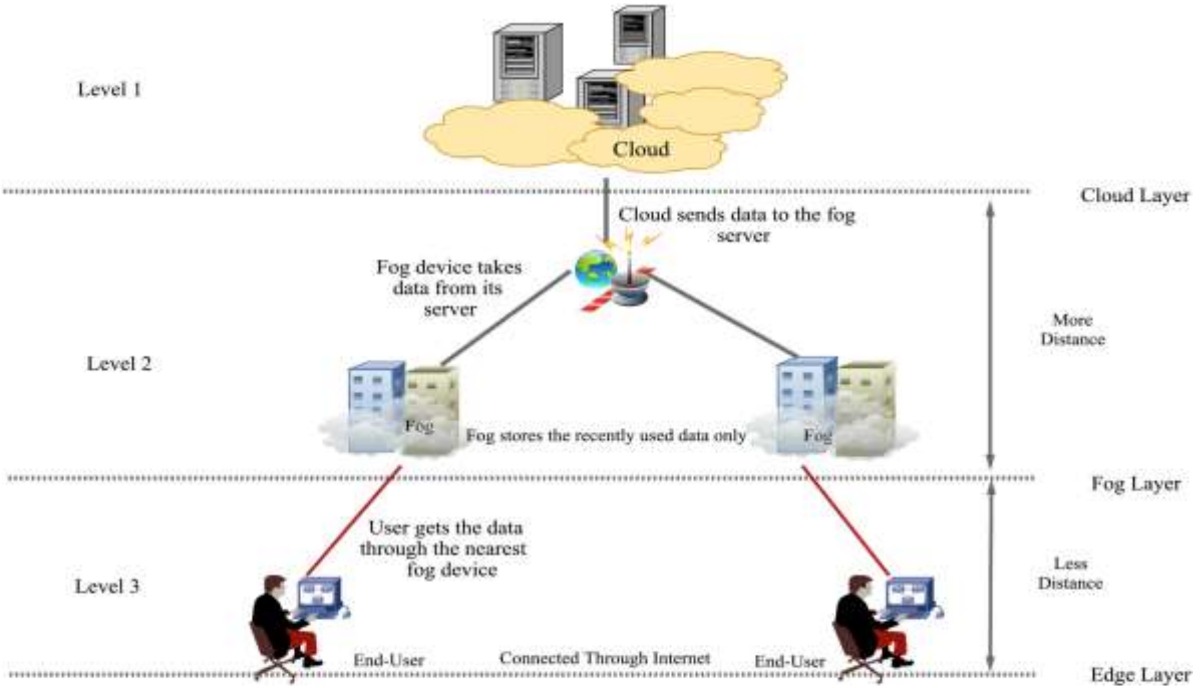

Figure 1 An overview of Fog computing. Kunal [7]

2. Related Works

Remote Health Monitoring System also called Remote patient monitoring (RPM) or Homecare Telehealth is an integration of embedded sensors, data repository, network facilities, application software, and other devices for data communication to enable monitoring of patients outside of conventional clinical settings. Among various applications of the Internet of Things (IoT) today, IoT-based Health Monitoring System seems to have gained more focus. The use of various physiological sensing devices and the emergence of reliable low-power wireless network technologies have enabled the design of remote health monitoring systems.

These advanced biosensors can be either embedded into smartphones or any other dedicated devices, wearable such as textiles, watches, wristbands, shoes, belts, and glasses, etc. which are worn by the patients or be directly embedded into the body of the patients i.e. skin patches so as to continuously monitor their health conditions [8]. These parameters are integrated, aggregated, and mined to do the early prediction of diseases and help the patients get a quick response from the healthcare giver remotely without having needed to be physically present at the hospital. IoT wearable platforms can be used to collect the needed information of the user with its ambient environment and communicate such information wirelessly, where it is processed or stored for tracking the history of the user [9]. The result shows that the introduction of fog computing improves latency, computation, and reduces the security risk.

Umair *et. al.* [11] attempts to find out interesting patterns from data of heart disease patients by using three algorithms-Decision Tree, Neural Network and Naïve Bayes in two different scenarios i.e. *first scenario:* when all the attributes are used and; *second scenario:* when the selected most suitable attributes are used, to investigate the effects of attribute selection method on the selected algorithms, and to compare the results of the three algorithms. The result shows that the Naive Bayes algorithm outperforms the Decision Tree and Neural Networks in the domain of predicting heart diseases. The Naive Bayes classification algorithms have the highest accuracy of 82.914% among all.

Shen [12] identifies the key issues in data mining model, these include identification and addressing of smart objects, data abstraction and compression, data archive, index, scalability and access control for IoT data, data warehouse and its query language for multidimensional analysis, interoperability and semantic intelligibility for heterogeneous data of IoT, time-series level and event-level data aggregation, and privacy and protection problem in data.

Four data mining models were proposed for the Internet of Things, these are:

1. Multi-layer data mining model.
2. Distributed data mining model.
3. Grid-based data mining model.
4. Data mining model from multi-technology integration.

The four proposed models are deployed in Cloud computing which, compares to Fog computing (a dedicated computing network for IoT systems) has higher latency, weaker security measures, and lower mobility-support.

Nachabe [13] and Song [14] identify certain problems pertaining to IoT infrastructure: the need for interoperability and Heterogeneity management. Hence, Nachabe [13] proposed OntoSmart for data collection, processing, and management of IoT systems, which paves the way towards SaaS (Sensing as a service) paradigm where users can request any discovered service regardless of the underneath mechanisms (data collection and sensor configurations). The proposed architecture relies solely on semantic techniques to challenge the problem of heterogeneity within the same and different data systems, and at the same time uses the idea of web semantic web servers to provide SaaS solutions based on the multi-agent architecture in order to distribute the processing among different components. The result shows that by using semantic techniques within IoT, the raw data is annotated by semantic data representing a predefined semantic model to unify its description. In this way, the problem of interoperability between different systems is resolved.

Zolfaghar [15] Presents a study of big data-driven solutions to predict the 30-day risk of readmission (re-hospitalization) for congestive heart failure (CHF) incidents. The work proposes a distributed solution called-Big Data Framework for Risk of Readmission Predictive Modelling for information extraction, integration, and solutions for predictive modeling using distributed classification models.

Data extraction was done using Hive open-source data warehousing solution built on top of Hadoop, with the use of declarative language - HiveQL, which are compiled into MapReduce jobs that are executed using Hadoop. The problem of readmission is formulated as a supervised learning problem. The raw data is preprocessed into classifiable data by selecting predictor and target variables and identifying each variable type then encode them as vectors. Random forest is adopted in this work because, according to the authors, it can work with all types of predictors. The limitation of the work is the difficulty in determining the subset of attributes i.e. (predictor variables) that have a significant impact on readmission of patients. It also has high overhead for training thus costly for traditional tools such as R.

Joshi [16] sees IoT as the next generation of the Internet which will contain trillions of nodes representing various objects from small ubiquitous sensor devices and handhelds to large web servers and supercomputer clusters. The paper focuses on the research issues of IoT concerning the data mining and various existing data mining models for the Internet of Things (IoT) and presents a novel data mining model for the Internet of Thing which considers typical IoT challenges. The proposed model is comprised of five layers i.e. data collection layer, data management layer, data analysis layer, data processing layer, and data mining. The model is capable of mining massive data coming from the Internet of Things (IoT) environment as well as accessing local databases, centralized servers, and distributed databases

3. Methodology

This work uses a Grid-based computing approach to leverage on fog computing to mitigate high latency and data security challenges associated with cloud computing. Grid-based computing approach is a distributed computing infrastructure that enables coordinated resource sharing within dynamic organizations consisting of individuals, institutions, and resources [17].

It is best used for both data-intensive and compute-intensive tasks applications because it offers resources, services, and data access mechanisms that favour such. We used grid-based architecture to effectively manage the distributed nature of IoT devices which in turn is responsible for its data intensiveness, share network resources, and most especially, to allow the parallel application of ANN algorithm across grid nodes to reduce execution time and enable multiple local models for aggregation. Our method is composed of three different phases namely; data collection and integration, data analysis and aggregation, Data storage, prediction, and feedback. Figure 2 shows the block diagram of our model; it consists of the three phases above mentioned and how each of the phases complements one another.

A. Data collection and integration: Data from various dedicated body sensors are collected using Radio Frequency Identification system RFID (figure 2). RFID is a technology that uses radio waves to read and capture information stored on a tag attached to an object. Data, in this case, include Chest pain (CP), Blood pressure (BP), Cholesterol (Chol), Blood sugar (BS), Electrocardiography (ECG). RFID readers read the information stored in the RFID tag that is dedicated to sensors that read the physiological vitals through radio waves. The tag, however, transmits a unique Electronic Product Code (EPC) when in proximity to a reader. Each tag reading generates a tuple of the form (*EPC; location; time*) - a universal identifier that gives a unique identity to a specific physical object where the *location* is the place where the reader is positioned, and *time* is the actual time when the reading took place and communicate it through a wireless interface to a local data warehouse in that particular grid inside the fog. The reason for this is that posting these data directly to the Cloud for analysis and transmitting the response data back is not the right solution, because it requires a larger bandwidth, and the latency is high [6].

The data used in this work were downloaded from the heart-disease directory of the University of California, Irvine (UCI) Machine Learning. The data consists of 920 instances and 76 attributes but only 14 attributes are relevant and were used for training and testing the network. The data was pre-processed by filling the missing values with appropriate numeric values that correspond to the data structure. We also performed feature reduction by applying Principal Component Analysis (PCA). PCA performs a linear mapping of the underlying data to a lower-dimensional space such that the variance of the data in the low-dimensional representation is maximized. This allows techniques such as classification to be done in the reduced space more accurately than in the original space.

We applied standard scalar on the data to transforms data in such a way that its distribution will have a mean value 0 and a standard deviation of 1. The purpose basically, is to normalize the data within a particular range. Sometimes, it also helps in speeding up the calculations in an algorithm. The data was then partitioned into two – Train set i.e. the set of data that was used to train the network; this partition makes 70 percent of the total dataset. The test set i.e. the set of data that was used to test the trained data; this second partition makes 30 percent of the entire data.

B Data analysis and aggregation: The entire operation in this phase takes place inside the fog computing figure 2. At each local warehouse inside the fog, the Artificial Neural Network backpropagation algorithm is applied at the same time (in a parallel manner) for data analysis to take place. Because of the communication issue in the network partitioning algorithm of backpropagation, pattern partitioning is adopted in which the full neural network is duplicated at every node, and each node in the computer grid trains the neural network on a subset of the training set at each epoch. On the completion of the analysis at the individual warehouse, patterns (models) are formed from the trained data at each grid in the fog network, each of which is referred to as a local model and is different from one another; this is so because each copy of ANN works on an entirely different dataset.

The reason for developing separate multiple models first at each warehouse was to 1) divide the computational workload among multiple nodes and provide a quick computational analysis so as not to forfeit our latency reduction objective, 2) further aggregate the multiple models to achieve more accurate model by reducing the variance of the constitute models. After the formation of the local models, each of the models is collected and aggregated by using an ensembling process i.e. bagging algorithm also called bootstrap aggregation, where a different base model instance is created for each bootstrap sample and the ensemble output is the average of all base model outputs. For a given input i.e. the outcome is an average of all the models.

However, bagging is capable of reducing the variance of constituent models, it also takes care of instability in the algorithm applied. (An unstable algorithm is the one that produces large changes in the output hypothesis if small changes occur in the training data). The ensemble output is the average of all base model outputs. A more accurate model is globally formed by aggregating the smaller models formed at each local grid. This model, also known as the centralized model is situated in the cloud to provide global access for Predicting Coronary Artery Disease among the patients on that network.

Algorithm for bagging:

In each iteration *t*, *t*=1,…..T

Randomly sample with replacement *N* samples from the training set

Train a chosen “base model” on the samples

For each test example

Start all trained base models

Predict by combining results of all T trained models: Averaging

End for.

The fog is the bedrock of this method because it improves data security and eliminates high latency that would have been encountered in the case of cloud. It extends the applications, data, services, and computing power network of the cloud computing paradigm from the core to the edge of the cloud thereby bringing it closer to IoT device to enable the processing of IoT generated data near data sources.

C Data storage, prediction, and feedback: The ensemble output referred to as the centralized model is the average of all the local model outputs that were formed inside the fog. The centralized model in the cloud (figure 2) enables global access for Coronary Artery Disease prediction results and data warehouse querying.

The prediction takes place in the cloud by collecting data from individual patient and run it against the model. Individual patient data is identified by the *EPC* generated by the RFID tag mentioned above. Therefore, the prediction result is sent using the same identification method. The prediction result can be viewed over the web by the designated hospital personnel and/or the patient via devices such as laptops, tablet phones, or any device that is capable of accessing the web.

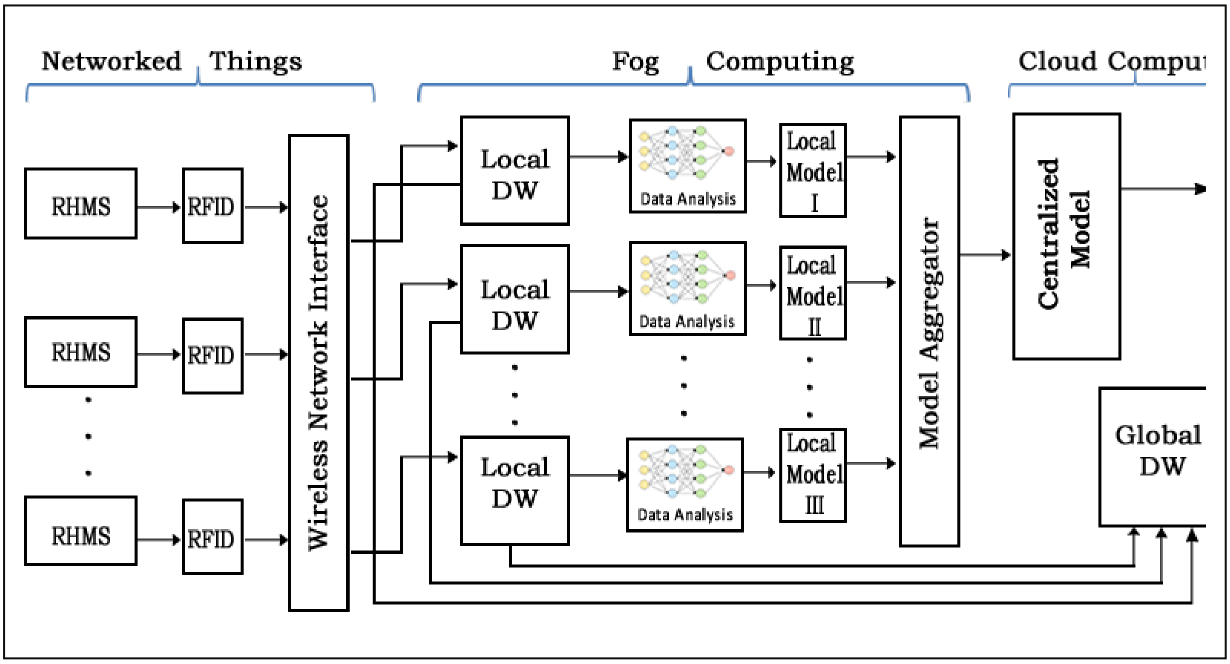

Figure 2 Grid-based prediction model for coronary artery disease

The cloud also serves as host for the permanent server - global warehouse, where data from local data warehouses at the individual node is collected and stored for permanent storage and for future purposes.

We compared our model with Ananda [11] which was developed to compare the following three algorithms; Decision tree, ANN, and Naïve Bayes in predicting the existence of heart disease using the same data set. The experiment was performed on two scenarios; 1) with attribute selection and 2) without attribute selection. The result shows that all the implemented algorithms with selected attributes performed much better than algorithms with all attributes except Naïve Bayes. In the Naive Bayes classifier algorithm, using all attributes shows the highest accuracy. Our model, however, which uses ANN backpropagation algorithm, out-performed the three algorithms in terms of accuracy and precision except for Naïve Bayes. See details in the Discussion below.

4. Result

The training of the network lasted for about 6-seconds. To make the result explicit, we used various performance metrics in evaluating our model; this includes confusion matrix which describes the complete performance of the model (see Figure 3), Equal Error rate, accuracy, sensitivity, precision, and ROC (Receiver Operative Characteristic) were also calculated and explained respectively. We calculated Equal Error Rate (ERR) as the number of all incorrect predictions divided by the total number of the dataset. The best error rate is 0.0 and the worst is 1.0 i.e. the lower the equal error rate value, the higher the accuracy of the model. Our Equal Error Rate is calculated bellow. Figure 4 shows the accuracy of our model which is also calculated as the fraction of predictions our model got right.

Our accuracy which is 81.32% implies that approximately 745 correct predictions were made out of 920 total examples. Figure 5 is a graph showing recall against precision. Precision, which was calculated as 0.8362 was used to determine how often the algorithm predicts correctly when it is actually correct; this implies that out of 281 positive cases, our model correctly predicted 235. Recall refers to the percentage of total relevant results correctly classified by our model. ROC (Receiver Operative Characteristic) graph was used to visualize the performance of the binary classifier; it determines how often the algorithm predicted correctly when the result was actually wrong. ROC curve helps us decide between different classifiers. See figure 6.

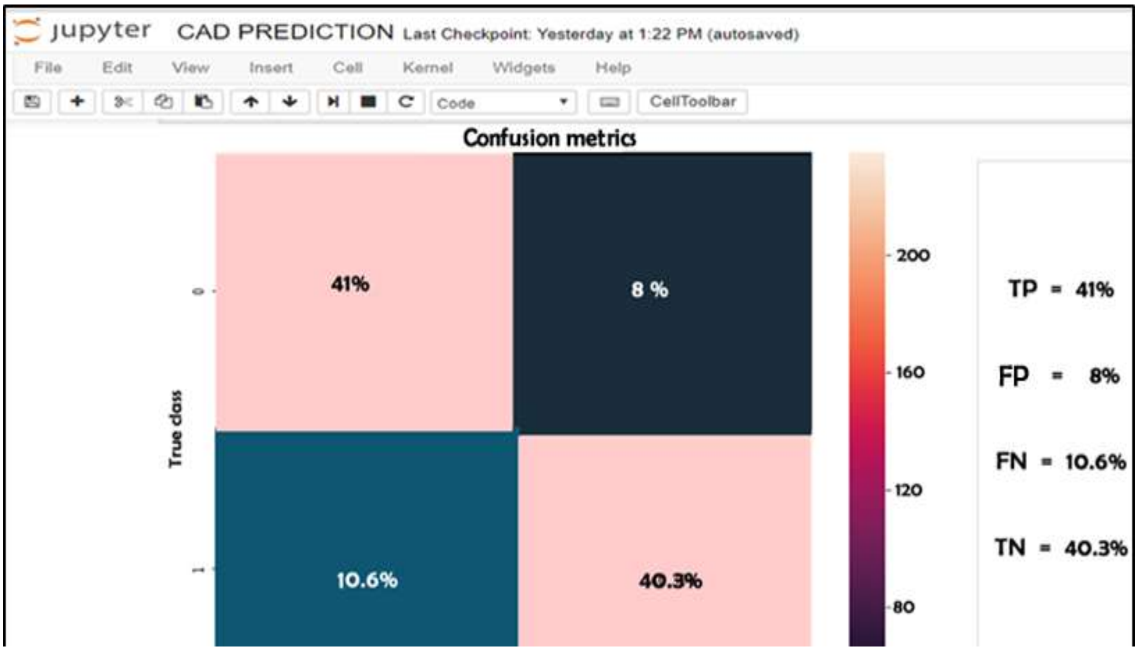

Figure 3: Confusion matrix

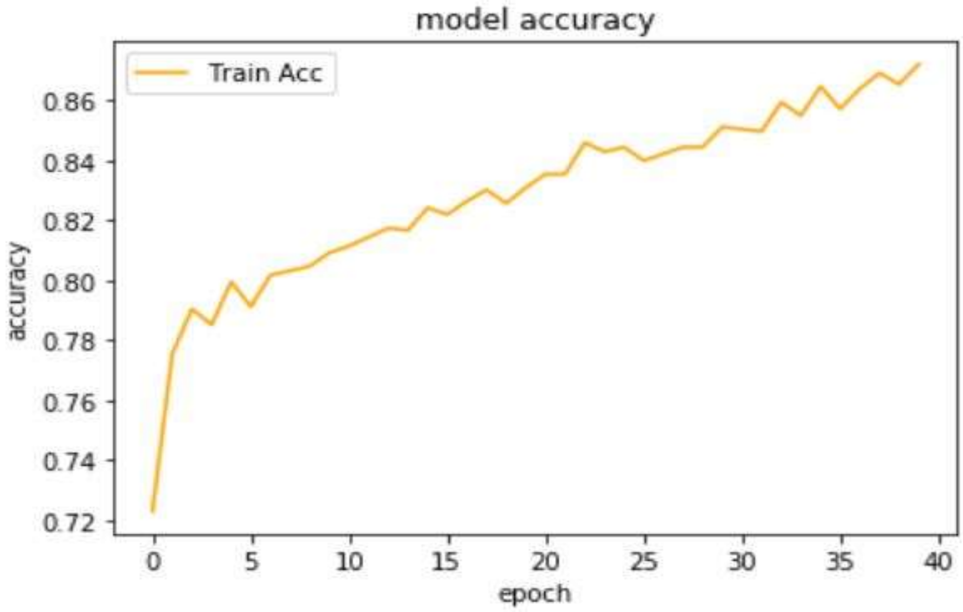

Figure 4: Accuracy

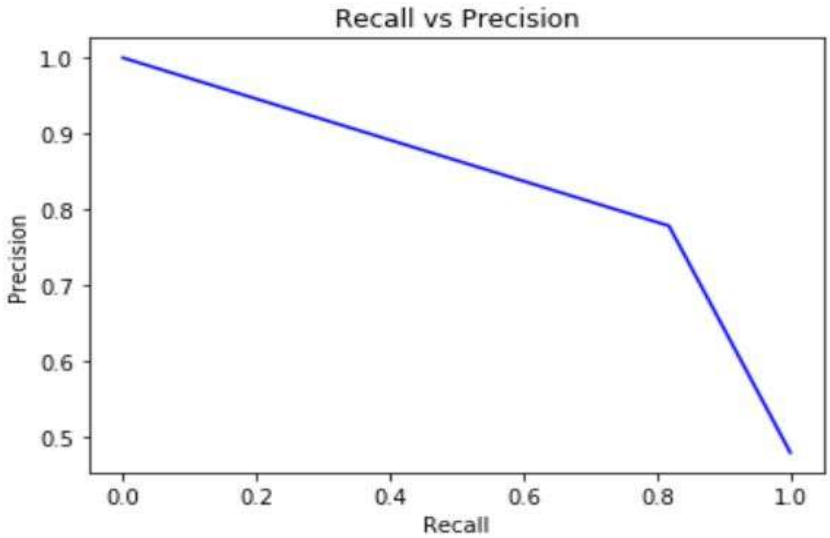

Figure 5: Sensitivity/Recall versus Precision

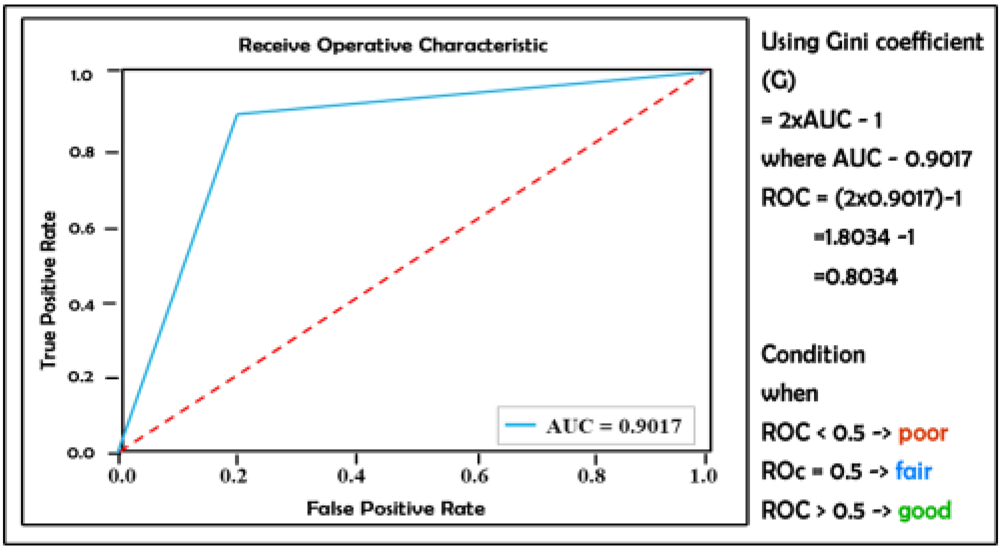

Figure 6: Receiver Operative Characteristic (ROC)

Equal Error rate

ERR = **(**(FP+FN) **/** (TP+TN+FN+FP)**)**
= (FP + FN)/(P+N)
= (46 + 61) / (371 + 292)
= (107) / (573)
= 0.1867 OR 18.67 %

Sensitivity:

SN = TP / (TP + FN) = TP / P
= (235) / (235 + 61)
= (235) / (296)
= 0.7939 OR 79.39 %

Accuracy:

$$\frac{\text{Total number of correct predictions}}{\text{Total number of prediction}}$$

= (TP+TN) / **(**(TP+TN)/(TP+TN+FP+FN)**)**

= (TP + TN) / (P + N)

= (235 + 231) / (281 + 292)
= (466) / (573)
= 0.8132 OR 81.32 %

Precision:

PREC = (TP) / (TP + FP)
= (235) / (235 + 46)
= (235) / (281)
= 0.8362 OR 83.62 %

5. Discussion

In our result, we used a confusion matrix to visualize the performance of our algorithm; the matrix shows the actual and predicted labels from a classification problem**.** It reports the number of false positives (FP) - incorrect positive prediction, *false negatives (FN)* - incorrect negative prediction, *true positives (TP)* - correct positive prediction, and *true negatives (TN)* - correct negative prediction. True positives are patients who are classified as positive “having heart disease” by our model that actually are positive i.e. correctly predicted outcomes; this gives us approximately 377 instances of the entire data.

False positives are cases our model incorrectly labels as positive “having heart disease” that are actually negative “not having heart disease”; this gives us approximately 74 instances of the entire data. True negative and false negative give us approximately 370 and 98 of the underlying data respectively. We used accuracy to know the ratio of the correctly predicted patients to the whole pool of patients. The accuracy value 0.8132 implies that our model is 81 percent accurate, that is, approximately 745 correct predictions were made out of 920 total instances.

Accuracy is a great measure when there is symmetric datasets i.e. where values of false positive and false negatives are almost same i.e. our false positive and false negative are 0.8 and 10.6 respectively. Equal Error Rate determines the percentage of the patient that was predicted incorrectly i.e. 18.67%, this implies that approximately 172 patients out of 920 were wrongly predicted – these comprise of both the false positives and false negatives. We used Receive Operative Characteristic ROC to calculate the overall performance of our model. We quantified the model by calculating the total Area under the Curve (AUC).

Having fully explored and implemented this model, the performance of our model was examined and compared with Ananda [11] which attempts to find out interesting patterns from data of heart disease patients using Decision Tree, Neural Network and Naïve Bayes in two different scenarios i.e. first scenario: with attribute selection; second scenario: without attribute selection. The result shows that the Naive Bayes algorithm outclasses the Decision Tree and Neural Networks in the domain of predicting heart diseases. The Naive Bayes classification algorithms have the highest accuracy of 82.914% among all; however, we found out that our model which uses ANN backpropagating algorithm out-performed the model in terms of accuracy and precision see Table 1.

Table 1: Result comparison

	Accuracy	***Precision***
Decision tree	0.7906	0.789
ANN MLP	0.8040	0.789
Naïve Bayes	0.8207	0.820
Our model (ANN) (Backpropagation)	0.8132	0.8362

6. Conclusion

The overall objective of this study is to develop a prediction model for coronary artery disease on fog network to mitigate high latency and data security challenges associated with cloud computing, using Artificial Neural Network and compare the performance of the model with an existing similar model Ananda [11]. In this study, a grid-based architecture was designed; the architecture which can collect data from the existing health monitoring systems using RFID technology and develop a prediction model for predicting coronary artery disease among patient using artificial neural network backpropagation. The process involves the extraction of data from the existing Health Monitoring Systems using RFID, data analysis, and model aggregation using bootstrap aggregation-bagging and lastly, data storage, prediction and feedback. Our model was simulated on the Jupyter notebook using Python language. The performance of our model was examined and compared with a similar model in Ananda [11], we found out that our model which uses ANN backpropagating algorithm out-performed the model which uses Decision Tree, Neural Network and Naïve Bayes with attribute selection in terms of accuracy and precision

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