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Real Time Health Care Big Data Analytics Model for Improved QoS in Cardiac Disease Prediction with IoT Devices

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Abstract:

Purpose: the problem of big data analytics and health care support systems are analyzed. There exist several techniques in supporting such analytics and robust support systems; still, they suffer to achieve higher performance in disease prediction and generating the analysis. For a hospital unit, maintaining such massive data becomes a headache. However, still, big data can be accessed towards analyzing the bio-signals obtained from the human body for the detection and prediction of various diseases. To overcome the deficiency, an efficient Health Care Big Data Analytics Model (HCBDA) is presented, which maintains a massive volume of data in the data server.

Methods: The HCBDA model monitors the patients for their current state in their cardiac and anatomic conditions to predict the diseases and risks. To perform analysis on health care, the model has accessed the data location by discovering the possible routes to reach the source. The monitored results on blood pressure, temperature, and blood sugar are transferred through the list of routes available. The network is constructed with a list of sensor nodes and Internet of Things (IoT) devices, where the sensor attached to the patient initiates the transmission with the monitored results. The monitored results are transferred through the number of intermediate nodes to the monitoring system, which accesses the big data to generate intelligence. The route selection is performed according to the value of Trusted Forwarding Weight (TFW) and Trusted Carrier Weight (TCW). At each reception, the features from the packet are extracted, and obtained values are fed to the decisive support system. The decisive support system cluster the big data using the FDS clustering algorithm, and the classification is performed by measuring the feature disease class similarity (FDCS). According to the class identified, the method would calculate Disease Prone Weight (DPW) to generate recommendations to the medical practitioner.

Results: The unique Health Care Big Data Analytics (HCBDA) paradigm for patient-centered healthcare using wireless sensor networks and IoT devices was described. The patient's bio signals are watched in order to provide medical assistance. In comparison to the previous methods, the proposed approach helps to generate higher performance in disease prediction accuracy up to 96%.

Conclusion: The value of Trusted Forwarding Weight (TFW) and Trusted Carrier Weight is used to determine the route (TCW). Sensor based IoT values like Pressure glucose, pulse oximeter, and temperature etc. the following parameters like classification accuracy and false ratio are calculated based on efficient machine learning model. The crucial support system receives the values it receives after each reception together with the features that were derived from the packet. The classification is carried out by calculating the Feature Disease Class Similarity, and the decision support system

clusters the huge data using the FDS clustering technique.

Keywords: Decisive Support Systems, Health Care Units, DPW, TFW, TCW, FDCS, HCBDA.

1. Introduction:

The growth of information technology has been adapted for several problems. The medical industries use the growth of IT in several ways. The health care data has been maintained in different locations of any organizational units and it has been accessed through modern informatics solutions to produce different intelligence to the administrators. For example, the disease prediction and analysis has been performed by several units which use the data present in different data servers located geographically in different locations. However, the IT solution makes it possible to access the data from different locations to produce the intelligence.

The dimension of data also gets changed to another form named big data, which represent the huge in size but also in schema. The organizations maintain such big data in various location of any network, which can be accessed to produce intelligence towards decision making or anything. To provide access to the big data there are number of protocols has been discussed earlier by various researchers. Still, the methods suffer with various problems. The medical organizations maintain various big data in remote location which has been used to perform analysis to produce result to support decision making. Such data has been accessed through network communications with novel development.

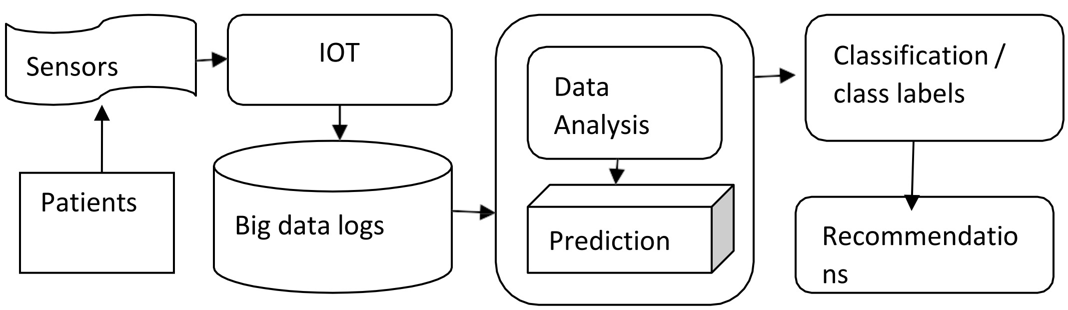


Figure 1: Process of Big data healthcare big data analysis

The development of communication technology has been adapted to various sectors. The same has been used in health care solutions, which support the data transmissions. Figure 1 shows the Process of Big data healthcare big data analysis For example, the health care data obtained by monitoring the patients of any hospital needs to be updated to a cloud or any dedicated data server, which in turn accessed by different units or medical practitioner towards decision making on what type of treatment can be given for the patients. For example, for a cardiac patient is recent most case disease condition suffered by patties, it is necessary to monitor the conditions of the patient at each time like blood pressure, temperature and blood sugar. By monitoring the conditions, the decision making can be performed.

The services are accessed through any network where the data transmission should be performed in efficient manner. In recent days, the IoT (Internet of Things) has been emerged as to be a part of various networks. When the IoT devices are identified in the WSN (wireless sensor network) they can be used to be a part of the route towards data transmission. When you consider the IoT devices, it is necessary to consider the security, and QoS performance of the network. This research is about the development of QoS of WSN towards accessing big data and how they can be analyzed towards health care. The main contribution of the work is to analyze the big datahealthcare records to predict the disease of the patients risks based on the feature and clusteringapproach.

The HCBDA model has been designed to support the decision making on the patient monitoring and providing effective treatment by producing decision making support to the administrators. Health Care Big Data Analytics Model (HCBDA) implements the data dimensionality reduction approach to analyze the healthcare records. The model clusters the data according to the FDS algorithm by measuring FDCS (Feature disease class similarity) value. According to the input signals and values, the method estimates disease prone weight for different diseases to come up with a solution. The same has been used to perform recommendations to the user. The detailed approach is presented in the next section, Section 2.

2. Related Works:

There are number of approaches discussed in literature towards health care monitoring and disease prediction. Such approaches are discussed in detail in this section.

(M. Mualuko , 2017) discussed a optimized fuzzy based ANT colony routing scheme which selects route according to the energy, traffic and distance. According to the values of above mentioned factors, set of fuzzy values are generated to measure the cost of route. The FACO approach selects the route according to the cost measured based on the above mentioned features. Similarly, (O. Deepa, 2017), presented an Optimized QoS-based Clustering with Multipath Routing Protocol (OQoS-CMRP) towards the reduction of energy depletion in improving service metrics based on data transfer rate. The method adapts Particle Swarm Optimization(PSO)-based clustering technique to frame the cluster. From the available routes, the method selects an optimal one according to the QoS metrics.

(Wenjing Guo, 2019) presented a reinforcement learning technique towards routing in WSN which finds the path to the destination and selects a route according to hop count, energy and distance. (N. Kumar and D. P. Vidyarthi 2018) discussed a Green Routing approach to support WSN where there are IoT devices become a part of that. The route selection is performed by considering different parameters and by applying PSO technique.

(Khan, I. Ali, 2018) presented a relay selection approach for UWSN which works on a cooperative manner. The method considers the depth of nodes and the distance based on location to perform route selection. Similarly, (P. Ramesh, M. Devapriya, 2018) discussed an energy efficiency path selection approach according to Lion Optimization Algorithm. (Govind P.Gupta, 2018) presented a Cuckoo Search-based Clustering approach (ICSCA) which selects the routes according to the energy of nodes and the distribution of nodes.

(Shahab Tayeb, 2018) presented a energy based cluster head selection which computes the credit for different nods to select optimal cluster heads (Muhammad Aslam, 2017) presented a adaptive immune Multihopping Multilevel Clustering (MHMLC) protocol towards the selection of cluster head where the CH should be within the range of base station. The HCA approach selects the route based on the energy and the distribution.

(Matheswaran Saravanan, 2014) presented a Bee Algorithm-Simulated Annealing Weighted Minimal Spanning Tree (BASA-WMST) is a routing scheme to manage the transmission gaps, which deploys random nodes. Similarly, (Deepa Onthachj, 2018) presented an Optimized QoS-based Multipath Routing (OQoS-CMRP) towards reducing the energy consumption.

(S. Jiang, 2018) presented the analysis of different protocol based on the LEACH Protocol for their performance in QoS performance. (G. Li and Lin Li, 2018) presented an Energy Balanced Routing scheme (EBRC) which cluster the nodes according to K means approach and adapts fuzzy system to select the cluster. Energy balanced routing scheme improves the data transmission without loss of the data to improve the IOT performance. Further, GA has been used to perform route selection. (Zhidong Zhao, 2018) presented a Energy-Efficient Clustering Routing Protocol based on AGNES which construct different clusters towards reduction of consumption minimization. According to that optimal route has been selected to perform data transmission.

(kokilavani 2020) presented a machine learning based disease prediction algorithm which uses synthetic dataset. (Bayu Adhi Tama, 2020) presented a CHD detection approach over machine learning which uses ensembles towards disease prediction. Similarly, a hybrid approach is presented to predict cardiac diseases with machine learning. The method combines several techniques towards disease prediction.

(R.S.M. Lakshmi Patibandla, 2020) presented a PSO based clustering development which uses generates higher cluster accuracy. (AhmedAl-Shammari, 2020) presented a density based clustering technique to support disease prediction based on the symptoms. (Theyazn H.H Aldhyani, 2020) presented a machine learning algorithm based disease prediction scheme which uses Rough K-means (RKM) clustering towards the detection of chronic diseases.

(Prabal Verma and Cygankiewicz 2018)described the IOT form of neural network algorithms to predict heart disease using the system learning machine proposed in this document. S. Lokesh and Adel Sabry Eesa (2020) defined the Perceptron (MLP) training data collection testing carried by IOT. (Sarmah and Kwok Tai Chui , 2020) In this methodology, for a produce output and one or more layers, where there are multiple layers of such inputs, these two inputs and outputs are hidden layer by layer

(U. R. Acharya and D. Lai 2020) described the risk identification cardiac disease based on classification which is connected to the neural node by these hidden layers. Some weights are assigned to this link. If the node is another identifiable input called bias, the features to balance any perceptron model.

(Prakash Mohan and T. D. Pham2019) described the Machine learning algorithms and techniques use machine learning techniques used in various clinical databases to automate the exploration of large and complex data for the prognosis of heart disease. Many researchers have recently been using various machine learning techniques to help medical professionals and diagnosticians in the field of heart related diseases.

(Jagadeeswari,and Adel Sabry Eesa2020) described the clustering based decision structures which is easy to understand the neural classifiers of methods of learning under supervision (H. Daniels,2010,and Prerana 2015). It handles both number and attribute datasets. The inner nodes of each branch consist of the branch and leaf nodes that represent the characteristic values of a given set of data and a decision tree, such as the tree structure with the experimental inner terminals. It was also found that the visual classes that see leaf projections or results show knots. Classification rules start from the leaf tip node, based on the predictive properties and some rules.

All the methods suffer to achieve higher performance in decision making and disease prediction accuracy.

3. Real Time Health Care Big Data Analytics Model for Cardiac Disease Prediction with IoT:

The proposed real time health care big data analytics model has been designed over wireless sensor networks which contains number of sensors and human sensors attached to the human body of any medical organization. Towards analysis with big data to support decision making, the IoT devices are considered which would support the communication to be performed in a continuous manner. The sensor data observed through the body sensors like temperature, pressure and blood sugar are transmitted to the decision support system through number of routes available in the network. The method consider number of IoT devices to complete the data transmission. On the other side, the selection of transmission route is performed by measuring a Trusted Career Weight (TCW) and Trusted Forwarding Weight (TFW). On the other side, the data are clustered using FDCS clustering and by measuring, FDCS measure the class of any input sample has been identified. Towards recommendation the method estimates the disease prone factor (DPF). The detailed approach is presented in this section.

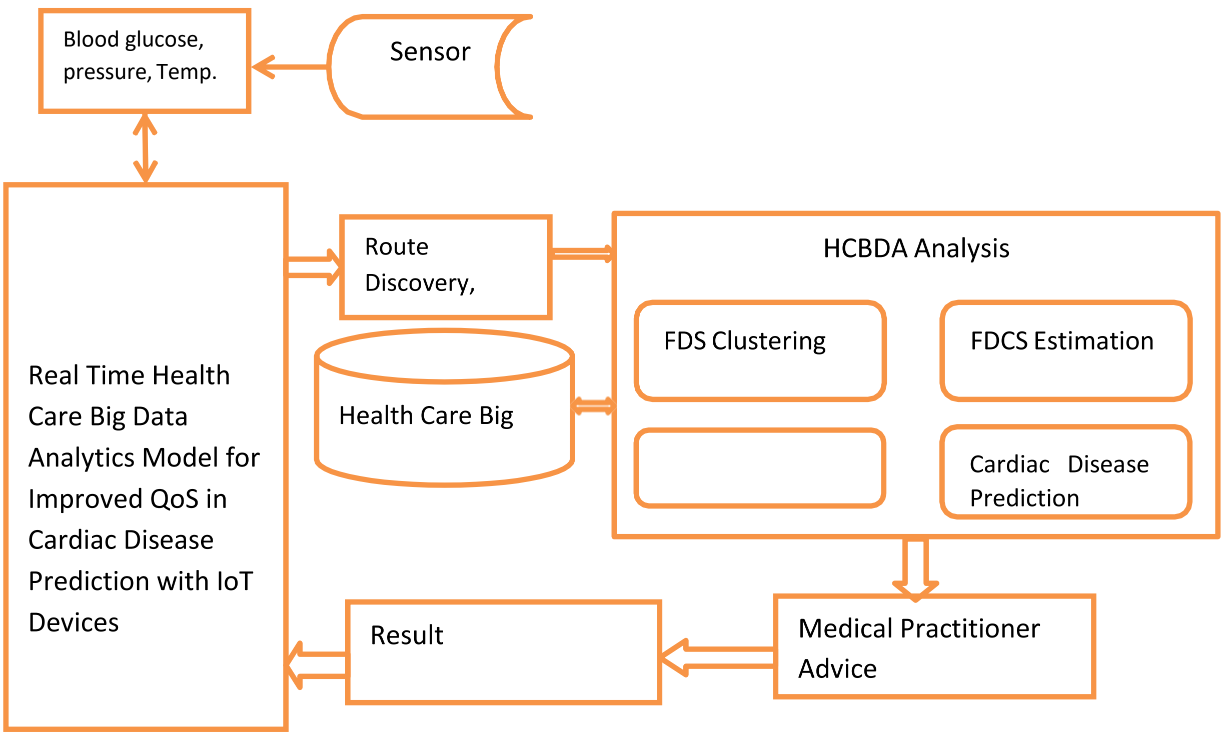


Figure 2: Architecture of Proposed Model

The functional architecture of proposed decision support system according to big data analytics is presented in Figure 2, the functional components of the model is discussed in detail in this section. The steps of the proposes system is explained by the following sections to evaluate the risk of big data model in healthcare data analytics.

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	70	1	4	130	322	0	2	109	0	2.4	2	3	3	2
1	67	0	3	115	564	0	2	160	0	1.6	2	0	7	1
2	57	1	2	124	261	0	0	141	0	0.3	1	0	7	2
3	64	1	4	128	263	0	0	105	1	0.2	2	1	7	1
4	74	0	2	120	269	0	2	121	1	0.2	1	1	3	1

Figure 3: cardiac patient dataset

The collection of features which is shown in cardiac dataset in figure 3 contains the collective information describes the various ranges of values.

Route Discovery & TCW Estimation:

The analysis of health care data is performed by accessing the decisive support system which runs on the support of big data available in remote site. To access the service and to perform the analysis, the method observe the bio signals through set of sensors attached to the human body and transmit the signals observed to the remote service. To perform this, first the method identifies the list of routes present in the route. The medical unit has been covered with wireless sensor network and to reach the destination there will be number of routes and each would covered by various sensor nodes and IoT devices. Towards this, the method generates the route discovery message and broadcast in the network. According to the reply, the method extracts several routes to reach the destination.

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak
count	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.00000
mean	54.433333	0.677778	3.174074	131.344444	249.659259	0.148148	1.022222	149.677778	0.329630	1.05000
std	9.109067	0.468195	0.950090	17.861608	51.686237	0.355906	0.997891	23.165717	0.470952	1.14521
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.00000
25%	48.000000	0.000000	3.000000	120.000000	213.000000	0.000000	0.000000	133.000000	0.000000	0.00000
50%	55.000000	1.000000	3.000000	130.000000	245.000000	0.000000	2.000000	153.500000	0.000000	0.80000
75%	61.000000	1.000000	4.000000	140.000000	280.000000	0.000000	2.000000	166.000000	1.000000	1.60000

Figure 4 : Marginal feature value Estimation

Figure 4 shows the average marginal value of cardiac principle Also, the method maintain the traces of previous communication. From the routes identified, for each of them the method computes the value of Trusted Forwarding Weight (TFW) and Trusted Carrier Weight (TCW). The TCW is the value measured for different intermediate nodes and the IoT devices. According to the TCW, the method would compute the value of TFW, based on which a single route is selected to perform data transmission.

Route Discovery and TCW Estimation Algorithm:

Input: Route Table RT, Node Table NT, Network Trace NeT.

Output: Route R

Start

Read RT, NT, NeT.

Generate HCBDBA-RREQ message = {Source ID, Destination}

Broadcast HCBDA-RREQ message.

While true

Receive HCBDA-RREP.

Extract routes and add to route table RT.

RT = $\sum$(Routes ∈ RT) ∪ (Route ∈ HCBDARREP)

End

For each route R

Find no. of IoT devices as Iots = $\sum$ IoT ∈ R

Compute Trusted Carrier weight TCW.

$$TCW = \frac{\sum_{i=1}^{size(NeT)} NeT(i).Route == R \;\; \&\& \;\; NeT(i).Route \in IoTs}{\sum_{i=1}^{Size(NeT)} NeT(i).Route == R}$$

Compute Trusted Forwarding Weight TFW.

$$TFW = \frac{\sum_{i=1}^{size(NeT)} NeT(i).Route == R \;\; \&\& \;\; NeT(i).Route \in IoTs \;\; \&\& \;\; NeT(i).Status == Complete}{\sum_{i=1}^{Size(NeT)} NeT(i).Route == R} \times TCW$$

End

Route R = Choose the route with maximum TFW.

Stop

The above discussed algorithm represents how the route for data transmission selected. The method estimates the trusted carrier weight and trusted forwarder weight for different routes. Based on the value of TFW a single route with maximum value has been selected to perform data transmission towards disease prediction.

FDS Clustering:

The feature depth similarity clustering is the procedure being used to group the big data under specific class names. As the dimension and volume of data is huge in size, it is necessary to group them under specific class. To perform this, the feature depth similarity clustering approach is presented. The method measures the similarity among the features in multiple level. According to the similarity, the method computes the feature depth similarity (FDS) according to the number of samples gets close on the feature and the total number of samples in any class.

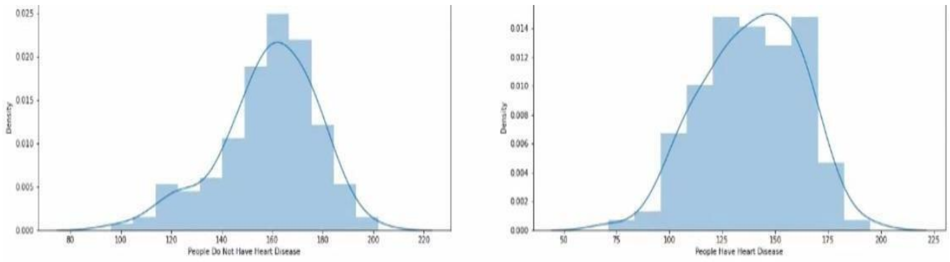


Figure 5: FDS clustering heart cardiac cluster and Non cardiac cluster

Figure 5 shows the FDS clustering heart cardiac cluster and Non cardiac cluster. Also, the number of features comes close for available number of features. Initially, a set of samples are assigned towards each disease class clusters and further the method computes the FDS measures to perform clustering.

FDS Clustering Algorithm:

Input: Data Set Bds

Output: Cluster Set Cs

Start

Read Bds.

Initialize number of clusters Nc = ∑ Disease Classes

For each disease class n

Assign random samples.

CS(n) = ∑ Random Sample (Bds)

End

For each sample s

For each cluster c

For each cluster sample cls

Compute Feature Depth Similarity FDS = $\frac{\sum_{i=1}^{size(S)} S(i).value==Cls(i).value}{size(S)}$

End

Compute cumulative feature depth similarity CFDS.

$$\text{CFDS} = \sum_{i=1}^{size(c)} C(i).FDS \Big/ size(C)$$

End

Cluster c = Choose the cluster with maximum CFDS.

Index the data point to the selected cluster.

End

Stop

The above discussed algorithm represents how the big data has been clustered according to the feature similarity. The similarity has been measured according to the depth of feature similarity available among different data points of any cluster. Based on the value of feature depth similarity, a single cluster has been selected and data point has been indexed to the selected cluster.

FDCS Estimation & Disease Prediction:

The data analysis is performed and disease prediction is performed by clustering the big data in both feature level similarity and dimensional similarity with the name FDS-Clustering. The FDS clustering algorithm measure the data point's similarity with each cluster according to the similarity in feature and dimension. Using these two, the method performs clustering which is used to identify the disease by measuring FDCS (Feature Disease Class Similarity). Based on the value of FDCS, a single disease class is identified and used to generate recommendations to the medical practitioner.

Algorithm:

Input: Cluster set CS, Test Sample Ts.

Output: Disease D

Start

Read CS, Ts.

For each cluster c

For each sample s

Compute feature disease class similarity FDCS.

$$\text{FDCS} = \sum_{i=1}^{size(s)} S(i).value == Ts(i).value \Big/ size(s)$$

End

Compute cumulative FDCS value = $\frac{\sum FDCS}{Size(C)}$

End

Choose the class with maximum FDCS.

Disease D = $\underset{i=1}{\overset{Size(Cs)}{Ma}}(Cs(i).FDCS).Class$

Stop

The above discussed algorithm shows how the disease prediction is performed according to the value of FDCS which is measured on different feature level similarity on various samples of different clusters available. According to the value of FDCS, the method selects a disease class with maximum FDCS value.

Recommendation:

Towards supporting the medical advisor or practitioner, the Decisive Support System measures the disease prone factor (DPF) based on the disease Prone Weight (DPW) towards each class of disease. If there is any match found for the current state, it has been classified and recommendations generated to the medical practitioner. According to the recommendation, the medical practitioner can recommend the set of treatment can be given to the patient. The value of disease prone factor (DPF) is measured according to the feature level similarity (FLS) measured on each sample available under the cluster. Based on that a set of recommendations are generated to the user.

Algorithm:

Input: Disease Class set Dcs, Cluster C, Test Sample s

Output: Recommendation R

Start

Read DCS, C

For each disease class dc

Compute disease prone factor DPF.

DPF = $\sum_{i=1}^{Size(C(dc))} Features(C(dc(i)) \equiv Features(s) \Big/ size(C^{(dc)})$

End

Choose the class C with maximum DPF.

For each treatment for class C

Compute success rate SR = $\sum_{i=1}^{size(C)} C(i).State == Success \Big/ size(C)$

End

Recommendation = Sort the treatment according to success rate.

Stop

The above discussed algorithm measure the disease prone factor for the given test sample s and measure the success rate for different treatment options to produce recommendation to the medical practitioner.

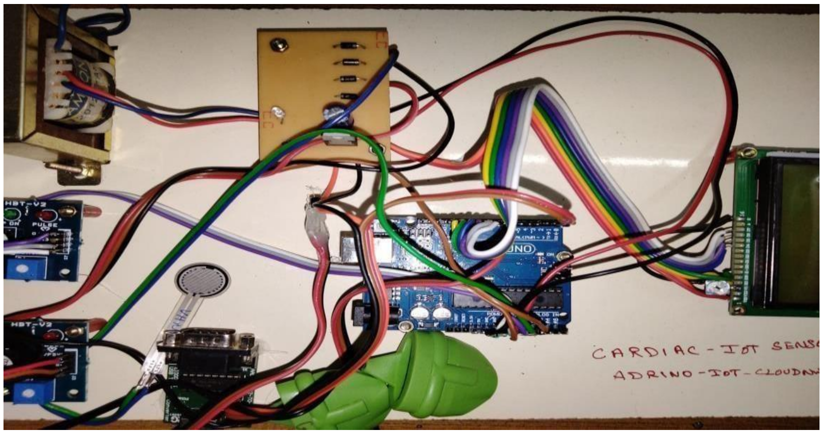
4. Results and Discussion:

The proposed approach has been implemented and evaluated for its performance under different parameters. The methods are measured for their performance towards disease prediction according to different features and their values. The result of evaluation has been analyzed with confusion matrix with existing approaches compared with the performance of other approaches. The results are presented in this section.

Parameter	Value
Language, Tool Used	Python, DevKit, IOT-LDA
Number of sensors	5(Cardiac principle Kit)
Number of features	30
Number of Sensors	20 (Simulated sensors)
Number of IoT devices in Network	30

Table 1: Evaluation Detail

The details used for the evaluation of performance produced by different methods are presented in Table 1.



The above figure 6 shows the simulation IOT kit which is designed based on the cardiac diseases monitoring principles. These collects the data from patients through IoT sensors make routing transmission into collective dataset.

According to this, the methods are measured for their performance in various parameters. The results obtained have been presented in detail in this section.

Routing Performance vs No of Nodes			
	30 Nodes	50 Nodes	100 Nodes
EBRP	68	72	78
BASA-WMST	72	76	84
OQoS-CMRP	75	81	88
HCBDA	84	88	94

Table 2: Analysis on routing performance

The performance in routing produced by different methods are measured and presented in Table 2, where the proposed HCBDA algorithm has produced higher routing performance than other approaches.

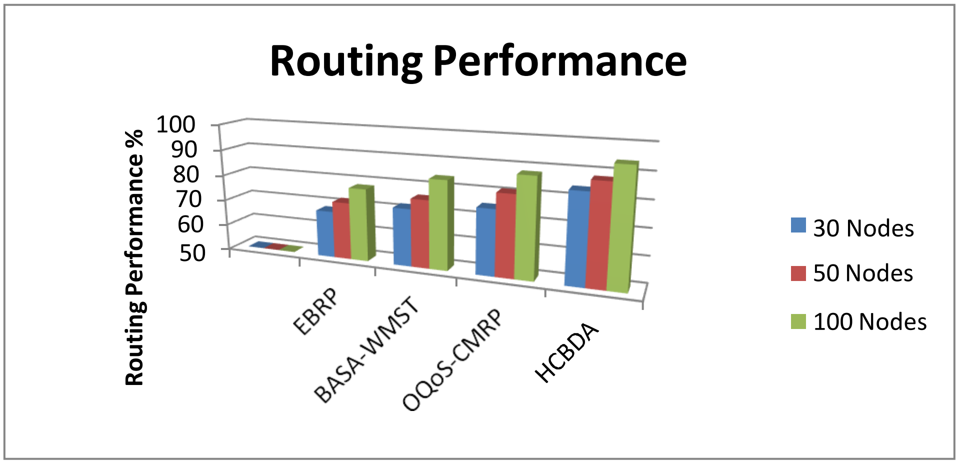


Figure 7: Performance in routing

The performance in routing introduced by different approaches at different number of nodes in the network has been measured and presented in Figure 7. The proposed HCBDA approach has produced higher routing performance than other methods in all the conditions.

Cluster Accuracy vs No of Patients			
Number of Records /methods	50	100	200
PSO	78	82	87
Density Based	82	86	91
RKM	85	89	93
HCBDA	88	92	96

Table 3: Accuracy in Clustering

The accuracy in clustering the big data towards disease prediction is presented in Table 3, where the proposed HCBDA approach has produced higher clustering accuracy than other methods.

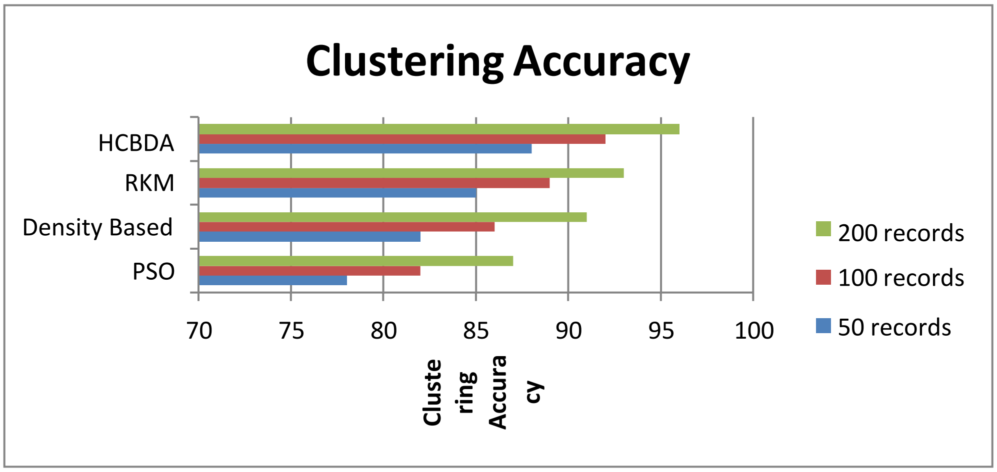


Figure 8: Accuracy in Clustering

The performance of clustering produced by different methods is presented in Figure 8. The proposed HCBDA approach has produced higher clustering accuracy under varying number of diseases considered.

Disease Prediction Accuracy vs No of Diseases			
Number of Records /methods	50	100	200
Machine Learning	65	72	77
CHD	67	76	81
Hybrid	71	79	83
HCBDA	86	91	96

Table 4: Analysis on Disease Prediction

The performance in disease prediction and its accuracy has been measured by considering different number of disease classes. The results obtained are presented in Table 4. The proposed HCBDA approach has produced higher disease prediction accuracy than other methods.

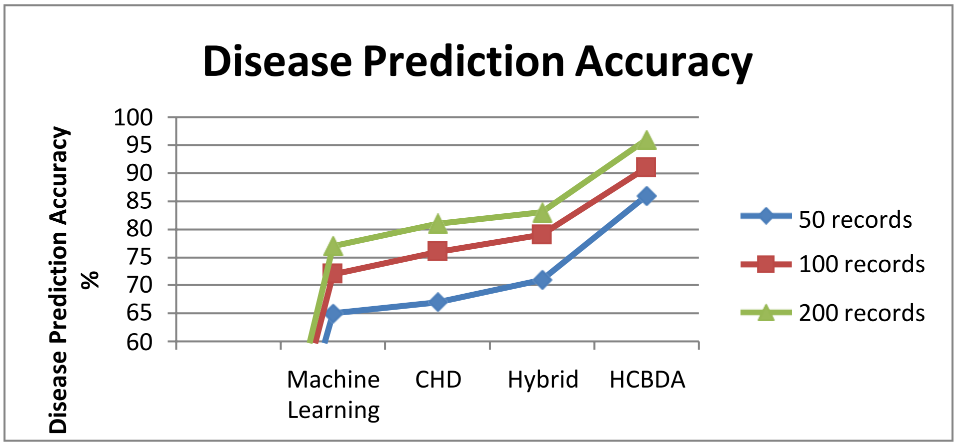


Figure 9: Analysis on disease prediction accuracy

The accuracy on disease prediction produced by different methods are measured and presented in Figure 9. The proposed HCBDA approach has produced higher disease prediction than other approaches in each class.

False Classification Ratio vs No of Diseases			
Number of Records /methods	50	100	200
Machine Learning	35	28	23
CHD	33	24	19
Hybrid	29	21	17
HCBDA	14	9	4

Table 5: Analysis on False Ratio

The ratio of false classification introduced by different methods are measured and presented in Table 5, where the proposed HCBDA approach has produced less false ratio than other methods.

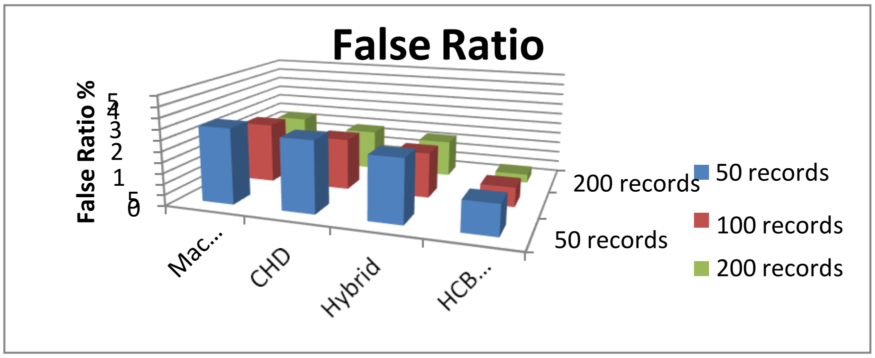


Figure 10: Analysis on False Classification Ratio

The accuracy on disease prediction produced by different methods are measured and presented in Figure 10. The proposed HCBDA approach has produced higher disease prediction than other approaches in each class.

5. Conclusion

This paper presented a novel Health Care Big Data Analytics (HCBDA) model towards health care support of patients with the support of wireless sensor network where there exist IoT devices. To provide health care support, the patient's bio signals are monitored. The proposed system contribute to produce higher performance in disease prediction accuracy up to 96 % than compared to the existing systems. The route selection is performed according to the value of Trusted Forwarding Weight (TFW) and Trusted Carrier Weight (TCW). At each reception, the features from the packet are extracted and obtained values are feed to the decisive support system. The decisive support system cluster the big data using FDS clustering algorithm and the classification is performed by measuring the feature disease class similarity (FDCS). According to the class identified, the method would measure Disease Prone Weight (DPW) to generate recommendations to the medical practitioner. The proposed method improves the performance of health care monitoring and decision making. In future direction the deep feature based classification approach is used to improve the classification accuracy.

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