Research Article

IoT with Cloud Based Distributed Disease Diagnosis System using Deep Belief Networks

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Abstract: Presently, Internet of Things (IoT) and cloud computing (CC) technologies offers a variety of applications and services in the medical field. In a distributed healthcare management, several IoT devices are utilized for monitoring the health condition of the people and forward the data to the cloud for examination. This study introduces an effective IoT and cloud based intelligent distributed disease diagnosis model using deep belief network (DBN). The presented DBN model primarily acquires the medical data from distinct resources. Next, the gathered data is sent to the cloud for further computation. The DBN model is implemented on the cloud to categorize the patient data into the presence of diseases. The DBN model helps to achieve proficient classifier results on the applied data. The results of the DBN model are examined under two medical dataset namely diabetes and heart disease. The experimental results demonstrated that the DBN model is found to be superior to existing methods by offering a maximum of 97.49% and 95.89% on the test diabetes and heart disease correspondingly.

Keywords: IoT, Deep learning, Cloud computing, Distributed system, Disease diagnosis, Healthcare

1. Introduction

In recent days, Internet of Things (IoT) has gained massive attention by developers, common peoples, and organizations. If traditional internet helps communication between restricted device and users, it states that all kind of objects are connected "Things" into broad web correlated with Computing Intelligence (CI) without user's knowledge. The approval of IoT and the development of wireless communication methods enable to send patient's health condition to physicians in real time (Abidi, B.; 2017). Besides, distributed computing in medical sector contains the collections of IoT relied medical tools as well as networking gadgets, that forwards and communicate the patient details to cloud server. In addition, diverse sensor and prominent device can determine specific physiological limits like Respiration Rate (RR) Blood Pressure (BP) and Heart Rate (HR) in a single tap. Yet, it is the first initial stage of deployment, business and firms have supported the management of IoT in this model, and the evolution is observed with user identity (Scuotto, V.; 2016). Yet, the integration of IoT model in medical application provides massive challenges and in combined as well as ubiquitous access, data controlling, security and privacy, replacement of data among devices and memory space. CC method is a feasible solution which place the report these promising issues. Fig. 1 implies a healthcare method which integrates with CC and IoT to offer the ability to share clinical details, well-known and clear structure globally, involved on-demand services by network, and perform few task that accomplish the requirement for deployment (Alam, M.M., 2018).

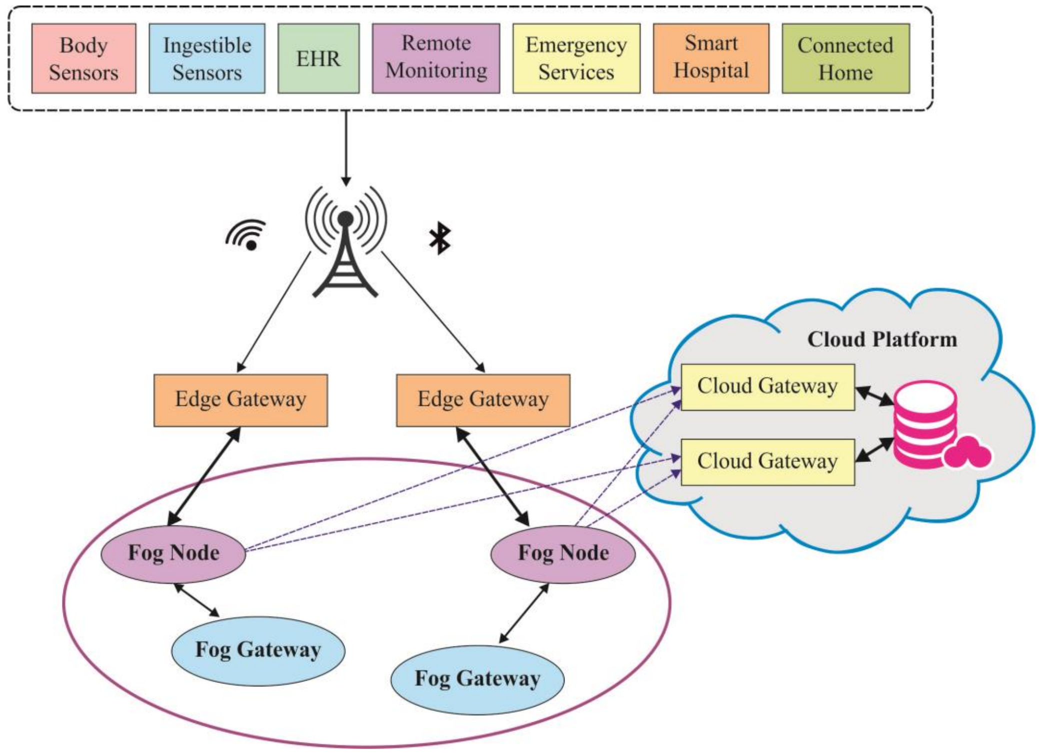

Figure 1. IoT based Healthcare scenario

CC takes IT services with data analytics, software, networking, databases, and servers using Internet to provide rapid procedures, responsive input, and financial scale. Moreover, the previous transition from centralized strategy of CC to decentralized theory (fog computing) contains topmost portions. Fog computing implements data analysis on edge gadgets, as it enables real time computation, deploys data security, and it reduces the expenses. The progressive development of CC, Artificial Intelligence (AI), and portable devices offers certain groundwork for IoT development in clinical application for modernizing all characteristics of individual lifetime. Followed by, (Stergiou, C.; 2018) applied an add insight regarding CC and fog computing methodologies, it is usual and functional scenario, massive challenges which occurs while applying CC and fog computing models with possibilities that is essential in future.

IoT provides an appropriate solution for diverse applications such as medical sectors, intelligent traffic management, supply chain, structural health observation, emergency services, retailing, modern cities, organizational management, trust, as well as waste management. According to CISCO, in future massive devices will be linked, that is equal to higher smart devices as per human being globally. By Dec 2017, IoT model have ensured the Statistic and developed a global IoT market which is around 8.9 trillion USD by 2020, and 7% of entire market worth come from medical application. The integration of IoT and CC in clinical field guides the care takers and physicians to provide best as well as effective health care facilities for optimal patient experience. Finally, it offers good health care services, patient identity, and reduces the text notes of medical experts.

The IoT in health care framework (IoTHeF) is realized as a basic feature of IoT in medical field as it intends for applying IoT and CC. It gives a best protocol to retain the interaction and broadcast original medicinal signal from diverse sensors as well as smart devices to web of fog nodes. It is composed of 3 significant objectives of IoTHeF that is composed of environment, infrastructure, and topology. Each module is facilitated as certain role in IoT medical frame. The system can collect data regarding patient condition through diverse sensors. Secondly, the gathered data has been provided to remote server for analyzing, and results are reviewed within a specific duration.

In last decades, various models were presented by researchers. (Prabal Verma, 2018) deployed a new method to monitor the disease level and analyze using CC and IoT. Such models are used for detecting the severity of disease. It is highly utilized to monitor the student's health state. In this approach, student health details are gathered from benchmark UCI Repository and from sensors used in medical applications that guides to predict the disease level. Different type of classification models have been used in distinct disease analyzes. The detection accuracy is determined using F-measure, specificity and sensitivity. Finally, it is apparent that the presented method outperforms better interms of prediction accuracy.

(Yunbo Li, 2018) developed a novel energy models that is operated dedicated service for CC based IoT environment. Such energy approaches have been employed for investigating the video streaming which is gathered from vehicles cameras. For estimating the system's effectiveness, these modules are applied in real-time for specific task and process the popular simulators to increase the function under the help of IoT machines. (Christos Stergiou, 2018) deployed a study on CC and IoT methodologies regarding privacy issues. Moreover, the major responsibility of IoT and CC has been defined exclusively. Finally, it is demonstrated that the key objective of CC in IoT is to improve the system's efficiency. (Ming Tao, 2018) introduced a new multi-layer cloud approach to enable the speed and seamless interoperations over the assorted facilities are provided by different vendors in smart home. Furthermore, ontology is used for resolving the heterogeneity issues which is presented in a layered CC platform. Moreover, it is used for addressing the data implication, knowledge as well as heterogeneity application. A security model was deployed and used the ontology for holding security and privacy preservation in interoperation’s tasks.

(PriyanMalarvizhi Kumar, 2018) established a new and scalable 3-tier structure to record higher number of sensor values. At the initial stage, Tier-1 proceeds data accumulation. Then, Tier-2 saves higher sensor details in CC. Eventually; a novel prediction model is employed for examining Heart Disease (HD). Followed by, ROC analysis is performed to identify the symptoms of HD. (Hyunsoo Lee, 2017) applied an effective Cyber Physical System to operate the multi-sites and multi-products deployment. (Chien-Hung Chen, 2017) used a novel system for car camera surveillance which applied mobile CC scheme for Deep Learning (DL). It investigates the objects in recorded videos which are obtained at the time driving a car and choose certain parts of video that has to save in CC. It is processed according to training phase, recognition phase and data collection phase. The best detection measure is obtained from this model.

(M.S. Hossain 2016) projected an online health observation system termed as Healthcare Industrial IoT. It is used for predicting the patients’ health condition and eliminates the mortality. The collected patient information is detected using sensors and medical devices. The key objective of this model is to remove clinical errors and diverse identity thefts with the application of security metrics such as watermarking as well as signal extensions. (Hussain, R. 32015) employed user relied sensing technique for old and handicapped people. The main aim of this method is to provide better service on the basis of emergency situations such as major accidents, heart attack, and pregnancy etc. (S.M.R. Islam, 2015) offered modern as well as collective security models to reduce the risks in IoT based healthcare application. Moreover, certain emphasis is offered to study the state-of-art network platform, applications and organization enhancement in IoT relied medical solutions. (R. Sethukkarasi, 2014) applied smart medical detecting model named as neuro-fuzzy temporal knowledge implication has been applied for the purpose of detection and diagnose various deadly disease.

This paper develops a new IoT and cloud enabled intelligent distributed disease diagnosis model using deep learning based deep belief network (DBN) model. The proposed DBN model comprises three levels namely data gathering, preprocessing, classification. At the earlier stage, the data gathering process collects the healthcare data of the patients from different sources. Subsequently, the acquired data is sent to the cloud server for extra computation, where the DBN model is applied for classifying the applied data into the presence of the disease. A comprehensive simulation analysis takes place to ensure the betterment of the DBN model and the results are examined under different dimensions.

2. The Proposed DBN Model

The overall process of the presented DBN method is illustrated in Fig. 2. The figure portrayed that the proposed DBN approach has initially undergo the data acquisition process in which data is collected from 3 diverse sources like electronic health records (EHRs), medical data with the help of IoT sensors that is fixed to human body and UCI repository data. Followed by, the gathered data is provided to cloud processing system in which data preprocessing and classification processes would be performed. The pre-processing stage removes the irregular data and enhanced the data supremacy. Consequently, DBN method is used as a classification method to find the existence of the disease in the medical data. The classified result is provided to alert system that embeds hospital database, physicians, and patients to be aware of medical output. The processes in these approaches are defined in the upcoming subsections.

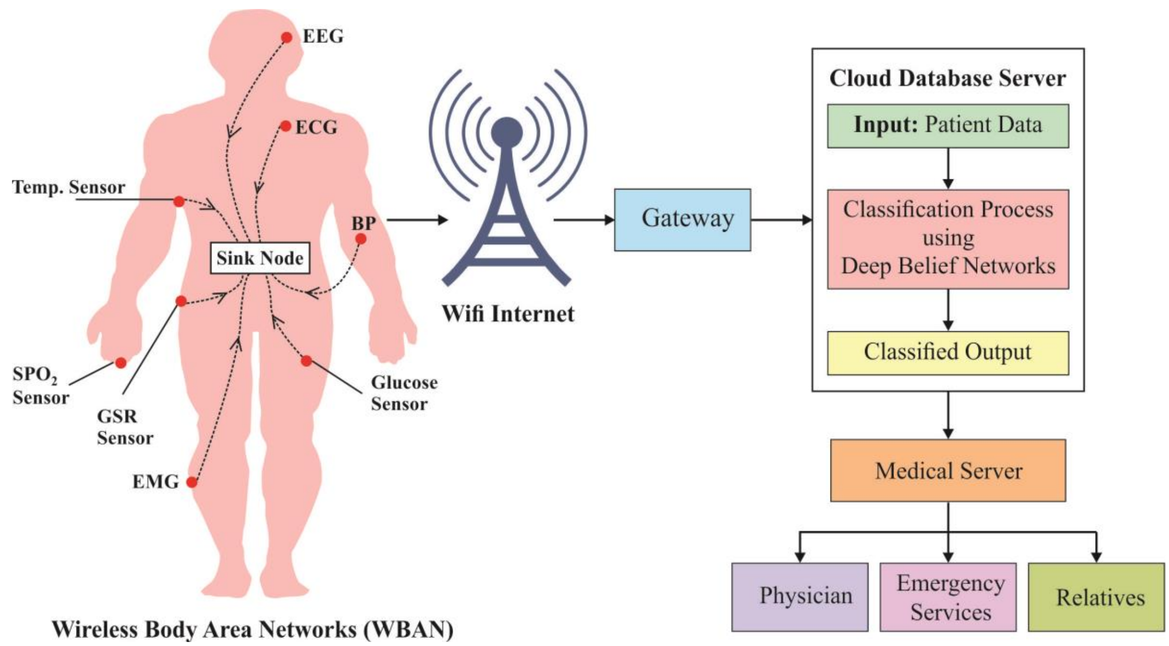

Figure 2. Working Process of Proposed Model.

2.1 Data acquisition and Preprocessing

Initially, the data is gathered under the application of IoT devices that is attached to human, EHR, and data repository. It is highly concentrated on the prediction of diabetes and HD. The IoT devices fixed on the human body gathers ECG, heart rate, BP, peripheral pulse oximetry (SpO2) level, glucose level, blood fat level, and pulse rate data for detecting HD. Followed by, glucose sensor, BP and pulse sensor have been applied for collecting data about diabetes disease analysis. If the data is collected, it is forwarded to CC processing unit. Moreover, while the data is accessible at cloud, preprocessing is performed. Initially, data transformation is carried out to transfer the data from categorical to arithmetical values. Secondly, normalization of data is carried out to change the data into uniform range.

2.2 DBN based Classification

RBM is an elegant NN approach while there is no separate layer and all neurons are bi-directionally attached with one another. The RBM contains a visible layer as well as hidden layer, as observed in Fig. 3. Followed by, a binary value has hidden n, visible neurons m and weights matrix W=(w_(i,j))×(m×n), that is the connection among h_i and x_i. RBM includes particular input and resultant layers and no connections are deployed among neurons. A major advantage of RBM-NN is that, it has to enable the neurons to be moved from one RBM network to another and served as input layer eventually.

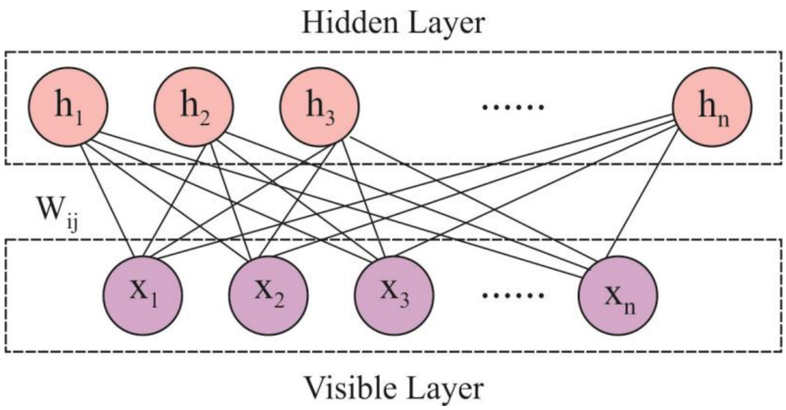

Figure 3. RBM Architecture

Basically, RBM is implied as visible layer x={0,1}^F and hidden layer h={0,1}^D. It is composed of power function, as illustrated in Eq. (1).

$$E(x,h) = -\sum_{i=1}^{F} a_j\, x_j - \sum_{j=1}^{D} b_j\, h_j - \sum_{i=1}^{F}\sum_{j=1}^{D} w_j\, x_j h_j \qquad (1)$$

$$= -a^T x - b^T h - x^T W h$$

where E(x,h) denotes the energy function, a and b are meant to are bias values of weights in hidden as well as visible layer. A probability function P(x,h) of RBM network is provided in Eq. (2).

$$P(x,h) = \frac{1}{Z} e^{-E(x,h)} \qquad (2)$$

where Z defines the normalization constant and signified by given equation.An increasing multi-level intrusion detection model utilizing hybrid-DBN

$$Z = \sum_{x',h'} e^{-E(x',h')} \qquad (3)$$

Moreover, the probability of a vector x is equivalent to the sum of equations over the hidden layers (Eq. 4).

$$p(x) = \frac{1}{Z}\sum_{h} e^{-E(x,h)} \qquad (4)$$

A following equation is utilized for distinguishing the probability of training data comparative to W. A suitable value of W is attained in the learning procedure.

$$\sum_{n=1}^{n=N} \frac{\partial \log P(x^n)}{\partial W_{ij}} = \alpha(E_{data}[xh^T] - E_{model}[xh^T]) \qquad (5)$$

where α implies the learning rate. E_data [·] ve E_model [·] indicate the predictable values in the data or model distribution.

2.3 Deep belief network (DBN)

In general, DBN is applied for DL methods, which is defined as NN to typically utilize the construction blocks of RBM's and contains of several RBM (Fig. 4) methods [17]. RBM with one hidden layer, capturing features in the data is not the right direction. At this point, layer-wise learning produces DBN. Then, a feature of DBN input data is removed. From the initial stage of DBN, it has layered RBM methods named as Logistic Regression (LR) which is depicted as the final outcome.

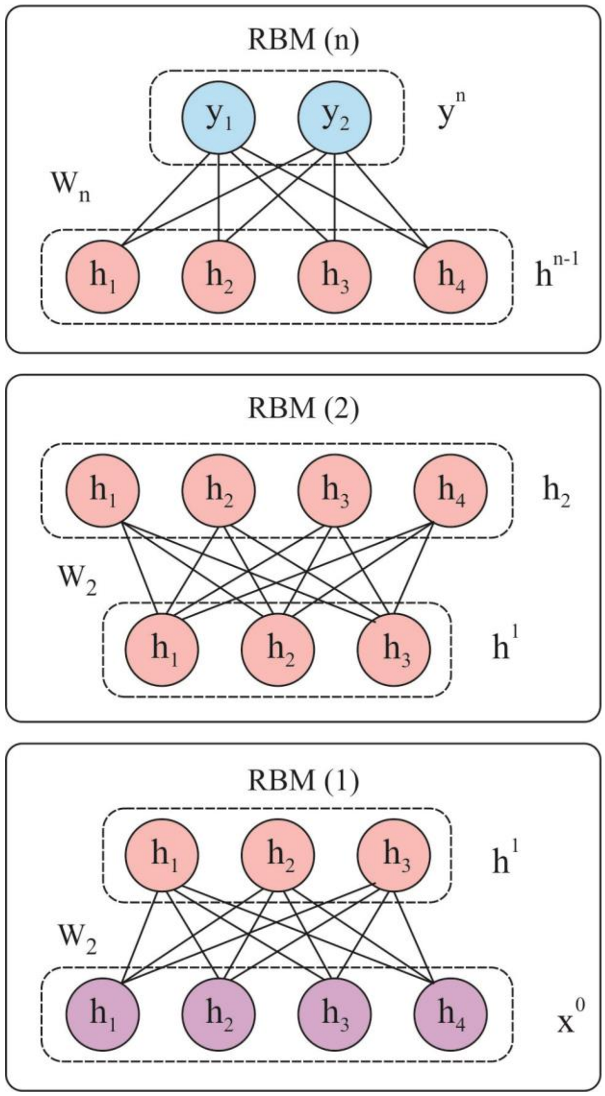

Figure 4. Architecture of DBN model

The BP is highly applied for training actual Artificial Neural Network (ANN). When the system is composed of higher nodes, the BP model perform in lower optimizations. The solution to these issues can be produced and it is accomplished by using pre-training model. Secondly, sampling has been used for pre-training the RBM approach and DBN present in the greedy layer. When the classification operation is carried out in DBN network; it can be applied by alternate learning process such as pre-training strategy, diverse learning that fine-tunes parameter application. Hence, unsupervised pre-process in greedy layer-wise type, h^K (x) is a representation of abstract x in the k layer.

In order to attain best individual function, modelled data has been applied to get an exact parameter space W. The adjustments are developed by adding consequent layer of variables training for required label instances from training dataset. Thus, optimization task is depicted in the following equation:

$$f(h^K(X), Y) = \sum_{i=1}^{n}\sum_{j=1}^{c} T\left(h^K\left(x_i^i\right) \times y_i^j\right) \quad (6)$$

where T signifies the loss function. A squared error function is usually utilized in BP, whereas the loss function is as following.

$$r = h^K\left(x_i^j\right) \times y_i^j \quad (7)$$

2.4 Softmax classification

The softmax classification is an extension of LR, which is utilized in several classifications. Here, labels are regarded binary y^((i))=∈{0,1}. A softmax classification is given by y^((i))=∈{0,N}. While N is the entire count of classes. The softmax contains input, classifier and Output Units, as depicted in Fig. 5.

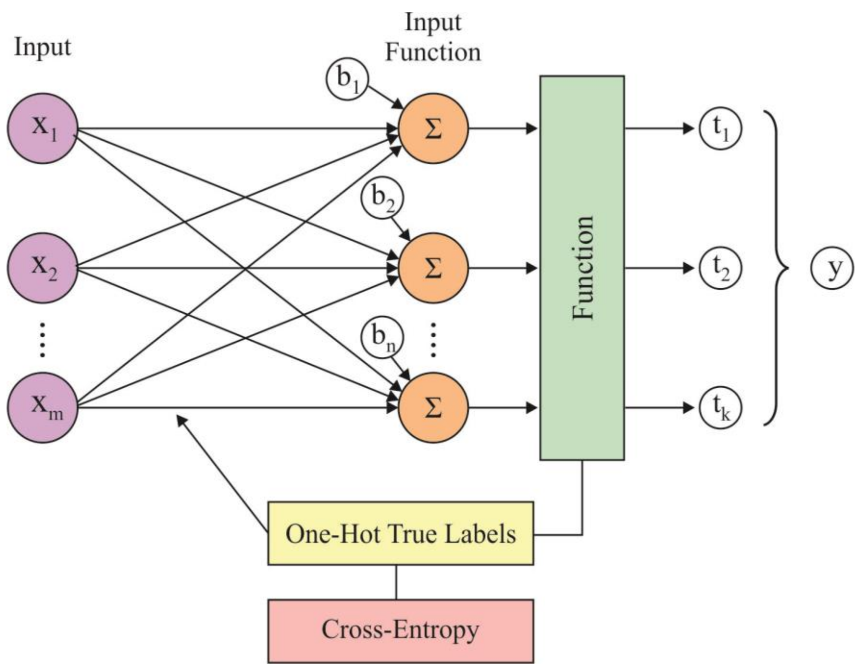

Figure 5. Softmax Classification model

3. Performance Validation

The experimental validation of the proposed DBN model takes place on two benchmark heart disease and diabetes dataset. The performance measures used to examine the results of the DBN model are sensitivity, specificity, and accuracy.

3.1 Analysis of DBN results on Diabetes dataset

Table 1 and Fig. 6 demonstrate the comparative examination of the classification results attained by DBN model interms of sensitivity. The figure portrayed that the SVM and NB models shows ineffective classification outcome by attaining lowest sensitivity values. Followed by, the KNN and DT models have reached to slightly higher and closer sensitivity values. Along with that, the FNC and IPSO-SVM models have exhibited somewhat acceptable and nearer sensitivity value. The EHO-KELM model has showed near optimal classification results whereas the DBN model has showed superior results over all the compared methods. For instance, under the record count of 2000, the proposed DBN model has reached to a maximum average sensitivity of 97.10% whereas the KNN, NB, SVM, DT, FNC, IPSO-SVM and EHO-KELM models have led to a lower sensitivity values of 92.00%, 87.50%, 83.00%, 93.00, 94.50%, 95.50% and 96.83% respectively.

Table 1Sensitivity Analysis of Proposed DBN with Existing Methods

No. of Records	**k-NN**	**NB**	**SVM**	**DT**	**FNC**	**IPSO-SVM**	**EHO-KELM**	**DBN**
2000	92.00	87.50	83.00	93.00	94.50	95.50	96.83	97.10
4000	88.00	86.00	82.50	92.00	93.50	94.00	96.54	97.32
6000	92.80	88.00	83.80	93.00	94.50	95.20	97.43	98.26
8000	93.50	88.00	83.00	97.00	98.00	98.70	98.94	99.13
10000	94.20	90.00	83.40	96.00	97.00	98.00	98.63	99.10
Average	**92.10**	**87.90**	**83.14**	**94.20**	**95.50**	**96.28**	**97.67**	**98.18**

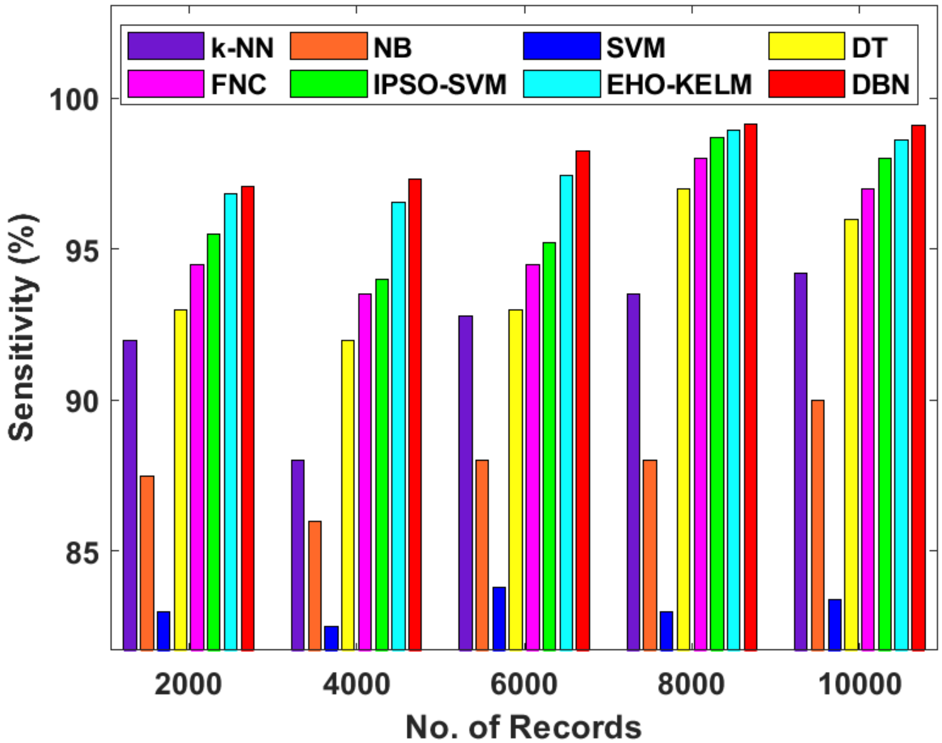

Figure 6: Comparative analysis of DBN model interms of sensitivity

Table 2 and Fig. 7illustrate the comparative investigation of classification results obtained by DBN approach with respect to specificity. The figure depicted that the SVM and NB methodologies have showcased inferior classification results by accomplishing lower specificity values. Besides, the KNN and DT methods have attained better and similar specificity values. In line with this, the FNC and IPSO-SVM approaches have illustrated moderate and closer specificity value. The EHO-KELM framework has depicted near optimal classification results while the DBN scheme has illustrated supreme results than the earlier approaches.

Table 2 Specificity Analysis of Proposed DBN with Existing Methods

No. of Records	k-NN	NB	SVM	DT	FNC	IPSO-SVM	EHO-KELM	DBN
2000	84.00	83.00	82.00	92.50	94.00	96.00	97.32	97.87
4000	90.00	83.00	83.00	91.00	94.20	94.80	96.86	97.54
6000	87.00	86.00	83.00	93.00	94.10	94.50	97.14	98.15
8000	87.50	85.00	80.00	88.00	90.00	91.00	94.89	95.67
10000	90.00	87.00	84.00	90.50	92.00	92.30	94.28	95.93
Average	**87.70**	**84.80**	**82.40**	**91.00**	**92.86**	**93.72**	**96.09**	**97.03**

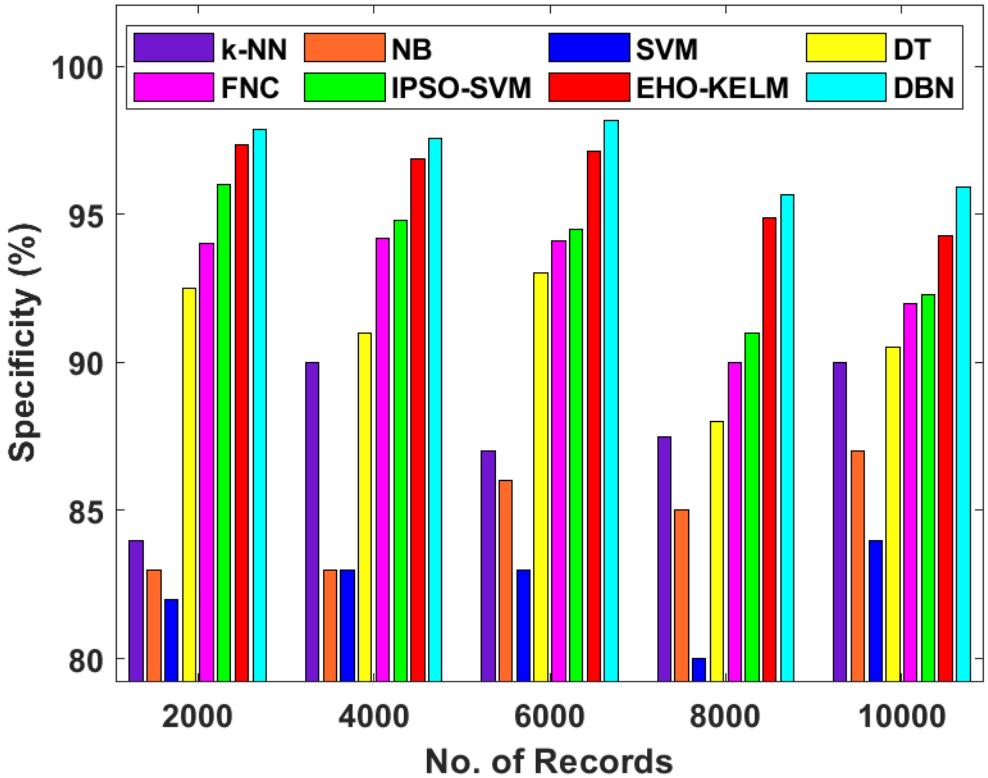

Figure 7: Comparative analysis of DBN model interms of specificity

For sample, under the record count of 2000, the projected DBN technology has accomplished higher average specificity of 97.87% and the KNN, NB, SVM, DT, FNC, IPSO-SVM and EHO-KELM approaches resulted in minimum specificity values of 84.00%, 83%, 82.00%, 92.50%, 94%, 96% and 97.32% respectively.

Table 3 and Fig. 8depict the comparative analysis of the classification results obtained by DBN model by means of accuracy. The figure implied that the SVM and NB approaches have demonstrated poor classification result by accomplishing minimum accuracy values. Besides, the KNN and DT approaches have attained better and closer accuracy values. In line with this, the FNC and IPSO-SVM models have implied moderate and closer accuracy value. The EHO-KELM technology has showcased near optimal classification results and the DBN scheme has depicted qualified results than the former methods. For instance, under the record count of 2000, the newly developed DBN approach has attained higher average accuracy of 97.98% whereas the KNN, NB, SVM, DT, FNC, IPSO-SVM and EHO-KELM models have provided minimal accuracy values of 89.00%, 77%, 74.00%, 92.00, 93%, 96% and 97.13% correspondingly.

Table 3 Accuracy Analysis of Proposed DBN with Existing Methods

No. of Records	k-NN	NB	SVM	DT	FNC	IPSO-SVM	EHO-KELM	DBN
2000	89.00	77.00	74.00	92.00	93.00	96.00	97.13	97.98
4000	91.00	81.00	76.00	94.00	94.00	94.00	95.78	96.52

6000	87.00	76.00	75.00	90.00	91.00	92.00	94.17	95.90
8000	88.00	82.00	78.00	93.50	94.50	95.00	97.56	98.60
10000	90.00	83.00	80.00	92.50	94.00	95.20	97.32	98.43
Average	**89.00**	**79.80**	**76.60**	**92.40**	**93.30**	**94.44**	**96.39**	**97.49**

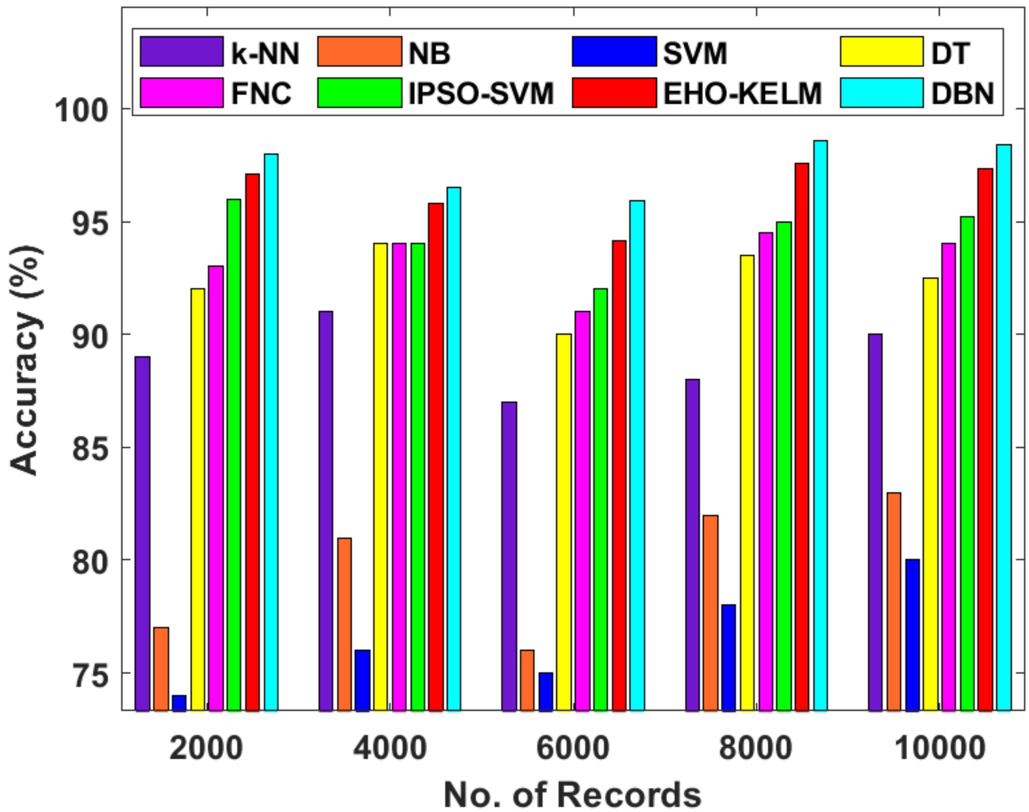

Figure 8: Comparative analysis of DBN model interms of Accuracy

An average analysis of classifier outcomes are demonstrated in Fig. 9. The figure clearly implied that the presented DBN approach has accomplished higher sensitivity, specificity and accuracy on the given diabetes dataset.

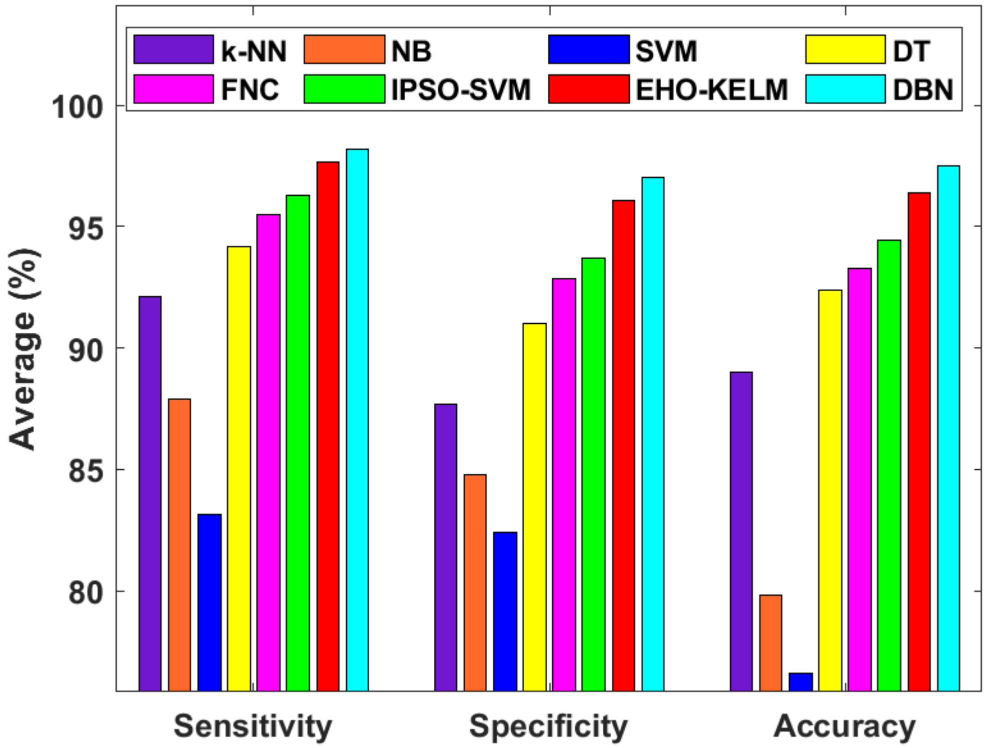

Figure 9. Average analysis of DBN model with existing methods

Table 4 and Fig. 10 illustrated the response time analysis of diverse methods. The figure indicated that the ANN scheme is said to be poor performer that needs high response time of 105ms.Then, the KNN method has achieved lower response time of 55ms. At the same time, the SVM method has offered moderate response time of 35ms. Hence, the NB and FNC frameworks have showcased manageable results over the predefined technologies with the response time of 23ms and 20ms. The IPSO-SVM and EHO-KELM frameworks have implied less response time of 17ms and 14ms. However, the projected DBN approach has represented a lower response time of 12ms.

Table 4 Response Time Analysis of Proposed DBN with Existing Methods

Methods	**Response Time (ms)**
SVM	35
ANN	105
NB	23
K-NN	55
FNC	20
IPSO-SVM	17
EHO-KELM	14
DBN	12

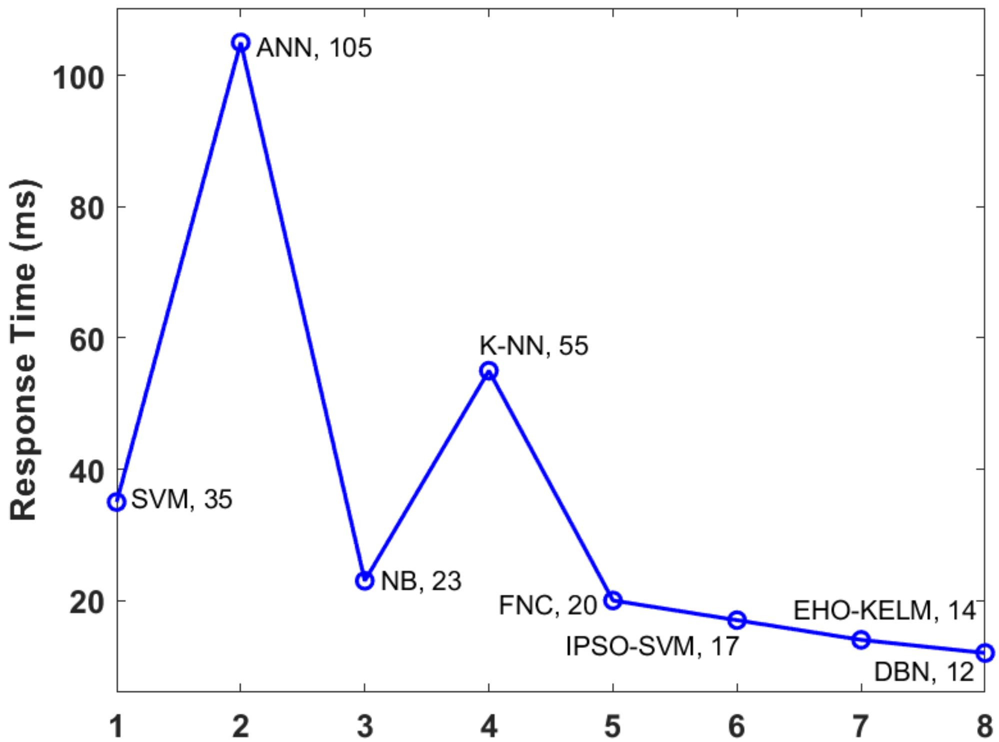

Figure 10. Response Time Analysis of DBN model with existing methods

3.2. Analysis of DBN results on Heart Disease dataset

Table 5 and Fig. 11 depicted the comparative investigation of the projected DBN model for HD detection interms of sensitivity, specificity and accuracy. The figure portrayed that the RT method is meant to poor performer that has attained lower value of sensitivity, specificity and accuracy of 74.40%, 71.11% and 72.93% respectively. Simultaneously, the MLP model has offered to reach moderate than SVM model, however not than alternate models with sensitivity, specificity and accuracy values of 78.40%, 79.52% and 78.87% correspondingly. Likewise, the RF approach has outperformed the former methods and showed considerable sensitivity, specificity and accuracy values of 81.97%, 82.44% and 82.17% correspondingly. At the same time, the LR model has illustrated moderate results over the RF with the reasonable sensitivity, specificity and accuracy values of 83.81%, 85.38% and 84.48% respectively. Followed by, the RBFNetwork approach has depicted higher performance with the nearby sensitivity, specificity and accuracy values of 85.18%, 81.56% and 83.49% correspondingly. Then, EHO-KELM has attempted to imply closer best results with sensitivity, specificity and accuracy values of 93.56%, 94.67% and 94.25% respectively. Hence, the proposed DBN model has reached higher classification performance which has proved the maximum sensitivity, specificity and accuracy values of 95.76%, 96.17% and 95.89% respectively.

Table 5 Result Analysis of Existing with Proposed DBN Method for Heart Disease Prediction

Methods	Sensitivity	Specificity	Accuracy
DBN	95.76	96.17	95.89
EHO-KELM	93.56	94.67	94.25

LR	83.81	85.38	84.48
MLP	78.40	79.52	78.87
RBFNetwork	85.18	81.56	83.49
RF	81.97	82.44	82.17
RT	74.40	71.11	72.93

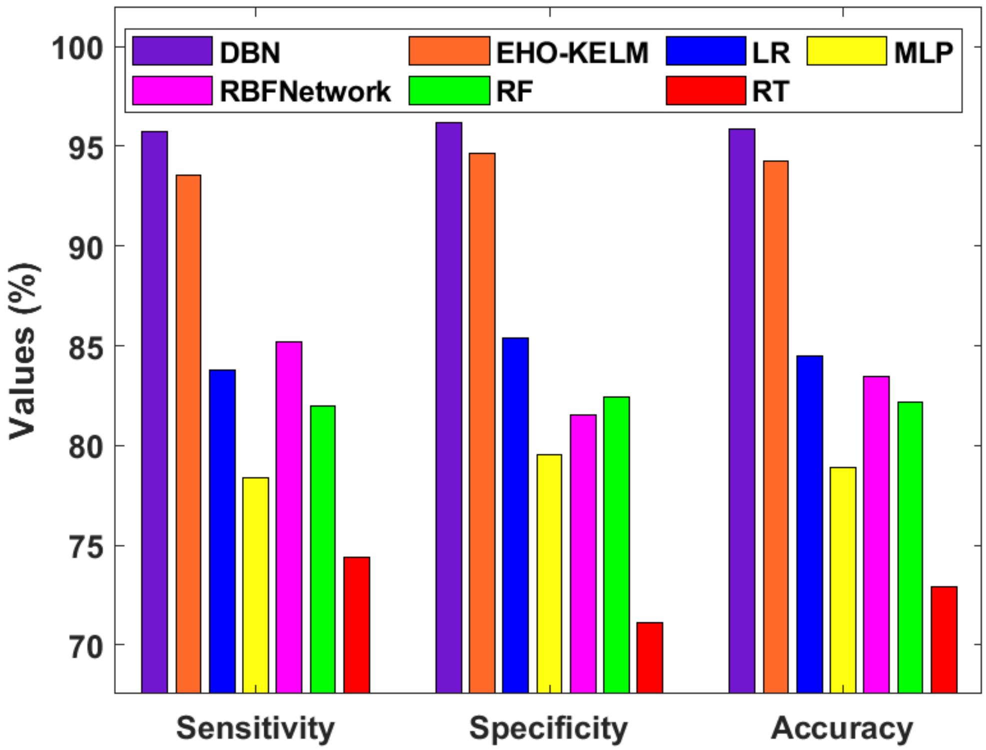

Figure. 11. Comparative analysis of DBN model for HD detection

3.3 Analysis of DBN results with recently proposed models

For future validation of supreme results of presented DBN model on applied HD dataset, a comparison of results have reached by the DBN method is performed with currently developed methods as given in Fig. 12. The DBN approach has attained higher classification function by accomplishing maximum accuracy of 95.89%. The predefined experimental validation assured that the DBN approach has performed quite-well than traditional approaches under various factors. Thus, it is applied as efficient IoT and CC activated prediction tool for disease diagnosis.

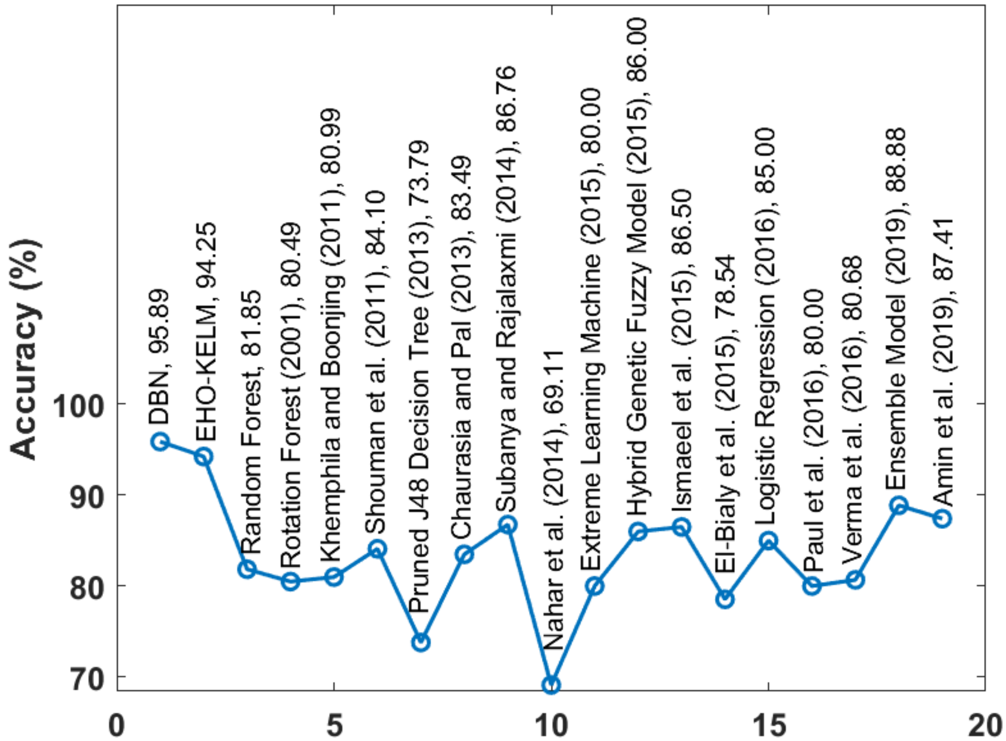

Figure. 12. Accuracy analysis of DBN with recent existing methods

4. Conclusion

This study has developed an effective IoT and cloud based intelligent distributed disease diagnosis model using DBN model.The proposed DBN model operates on three stages such as data gathering, preprocessing, classification. At the earlier stage, the data gathering process collects the healthcare data of the patients from different sources. Subsequently, the acquired data is sent to the cloud server for extra computation, where the DBN model is applied for classifying the applied data into the presence of the disease.The experimental results demonstrated that the DBN model is found to be superior to existing methods by offering a maximum of 97.49% and 95.89% on the test diabetes and heart disease correspondingly. In future, the performance can be increased by the use of feature selection and clustering approaches..

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