Deep Forest Based Internet of Medical Things System for Diagnosis of Heart Disease

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***Abstract*—Due to advancement in internet of medical things, the conventional health-care systems are transformed into smart health-care systems. The medical emergence services can be significantly enhanced by integration of IoMT and data analytic techniques. These technologies also examine the unexplored area of medical services that are still unseen and provide opportunity for investigation. Moreover, the concept of smart cities is not achievable without providing a smart connected healthcare scheme. Hence, the main purpose of this research is to come up with a smart healthcare system based on IoMT, Cloud and Fog computing and intelligent data analytic technique. The major objective of the proposed health-care system is to develop a diagnostic model capable for earlier treatment of heart disease. The suggested scheme consists of distinct phases such as data acquisition, feature extraction, FogBus based edge/fog computing environment, classification, and evaluation. In data acquisition, different IoMT such as wearables and sensors devices are considered to acquire the data related to heart disease and the various features related to signal and data are extracted. Further, the deep forest technique is integrated into the proposed system for classification task and effective diagnosis capabilities of heart issues. The performance of the suggested scheme is evaluated through set of well-defined parameters. Comparison with other healthcare model was conducted for the purpose of performance evaluation. It is concluded that the proposed model has a superiority over other all other models in different aspects namely, the sensitivity measure, accuracy measure, and specificity.**

***Index Terms*—Deep forest, Fog computing, Healthcare system, Heart disease, IoMT.**

I. Introduction

Recently, cloud and fog computing environments gain wide popularity and can be acted as main pillar in the toady economy due to on demand services to users through global network (Mutlag, et al., 2019). These computing paradigms have significant impact in industry as well as in academia. But due to delay response, cloud computing cannot be more appropriate in real time applications (Farahani, et al., 2018). Apparently, fog, IoT, edge, and big data have been exposed tremendously due to capability of less response time with respect to target applications (He, et al., 2017). These technologies provides better computations, communications, and storage for edge devices and also improved the variety of constraints such as latency, N/W bandwidth, mobility, privacy, and security. Through literature, it is identified that fog computing is more appropriate for latency sensitive and real time application (Rahmani, et al., 2018). At present, cloud computing frameworks also enhanced and provide more robust and reliable infrastructure and services for many applications (Gupta, Maharaj and Malekian, 2017). While, fog computing handles the issues such as energy consumption, n/w latency and response time through nodes, routers and gateways for offering better services. Other side, growth in IoT devices led to tremendous amount of data (Islam, et al., 2015). These devices are utilized into different domains such as transportation, healthcare, business, networks, industry, finance, and communication and having significant impact on users. In healthcare, these devices are widely adopted and deployed for obtaining the diverse data from users and further several techniques based on artificial intelligence, computer vision, deep learning, etc., are applied for analyzing the collected data (Gambhir, Malik and Kumar, 2016) (Singh and Kumar, 2019) (Kaur and Kumar, 2021) (Kumar, et al., 2019) (Gambhir, et al., 2019). This data analysis can be beneficial for designing and developing the efficient and robust healthcare model as well as earlier intervention, prevention and optimal management of health services. Fig. 1 illustrates the few applications of IoT devices. It is analyzed that collected data are in huge amount and existing tools are not capable to process and interpret such massive data (Srivastava, Kumar and Singh, 2022). IoT with data analytics, edge computing and fog computing are capable to provide state of art solutions for many healthcare applications such as health monitoring, diagnosis and prediction of diseases, emergence services, resource allocation, and elderly care. The objective of data analytics is to investigate the information of patients considering the medical tests and complications. Such information can be used for proper management of the disease and medication.

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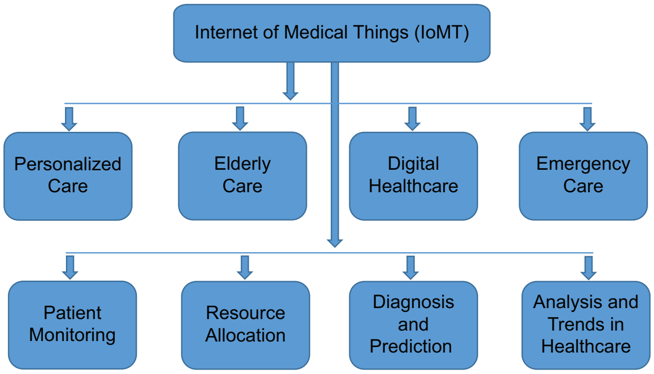

Fig. 1. Depicts the several applications of IoMT.

Further, the advance data management tools such as cloud computing, visualization can also facilitate to health organizations to develop platforms that can capture, store, and alter huge amount of data in effective manner. Other side, fog computing can be adopted in healthcare to get concise, precise and real time information for progressive improvements. Moreover, the incorporation of fog computing capabilities in the health-care application will improve the security as the resources will be close to users and this also helps to achieve minimum latency (*Machine Learning, Big Data, and IoT for Medical Informatics - Google Scholar*, no date). In turn, it can be beneficial to get earlier prediction and also enable essential and quick action for curing the critical disease patients. However, it provides the quick results, but has the challenge of complex data while at the same time it is required to provide precise results (Kumar, et al., 2018). Further, it is observed that several techniques have been considered for collecting the health-care data and it is acted in two ways:- (i) Get the data from input file and (ii) obtain the data from different IoMT devices (Kaur, Kumar and Kumar, 2019). It is noticed that more than 250 MB data/min is collected over the network (Satpathy, et al., 2020). However, the traditional techniques are not capable to capture and process the massive amount of data. This problem can be override by utilizing the fog computing capabilities. Data are collected and aggregated using smart devices over the IoMT network and it can be stored and processed either cloud server or edge nodes. Hence, the proposed system suggests to combine the IoMT, cloud and fog computing. The suggested scheme is summarized below.

To design a heart disease diagnosis system based on the IoMT, cloud and fog computing technologies, called decision support system (DSS).

The relevant information regarding the heart disease are gathered using the IoMT devices including signal data.

Signal features such as entropy, peak amplitude, and energy and data features, that is, mean, skewness, and kurtosis are extracted for accurate diagnosis of heart disease.

The diagnostic task is accomplished through optimized deep forest cascade technique.

The performance of proposed DSS is validated through a set of well-defined performance parameters.

II. Related Works

Mishra, et al., (2021) came up with a health-care monitoring system utilizing IoHT for detecting the lung cancer risk. The data are collected through patients using IoHT devices. The relevant attributes for lung cancer is identified using greedy best first search (GBFS) technique. Further, the symptoms of lung cancer are detected using the random forest technique. Simulation results indicated that GBFS-RF system obtains superior results in terms of accuracy (98.8%) and latency (1.16s) compared to other models. The suggested model is more sustainable in terms of energy sensitive and reduced overhead.

Khamparia, et al. (2021) presented an effective system for skin cancer classification\detecting. The proposed scheme is integrated IoHT, deep and transfer learning techniques to provide accurate skin cancer detection. The relevant features are extracted using the VGG19, Inception V3, ResNet50, and SqueezeNet techniques in automatic manner. These features are giving to the fully connected convolutional neural network (CNN) to determine the skin as benign and malignant. Moreover, the proposed framework is integrated with IoHT devices for assisting the specialist remotely to diagnosis the skin cancer. The efficacy of proposed framework is assessed through recall, precision, and accuracy parameters. The results stated that the proposed framework provides 99.20% of accuracy rate for detecting the skin cancer.

Vellameeran and Brindha (2022) designed the heart disease diagnosis system based deep belief network and wearable IoT medical devices. In the proposed diagnosis system, wearable devices are employed to get the relevant data from patient regarding the heart disease. Several features are extracted from the collected data such as skewness, kurtosis, and peak amplitude. Further, a hybrid algorithm called PS-GWO algorithm is utilized for computing the more relevant features from the extracted set of features. These relevant features are fed to the modified DBN to diagnosis of heart disease. The hyper parameters of DBN are also optimized using the PS-GWO technique. The performance of the heart disease diagnosis system is examined over three scenarios using accuracy parameter. It is reported that proposed diagnosis system achieves 88.8%, 87.1% and 83.8% accuracy rate with scenario 1, scenario 2, and scenario 3, respectively.

Mansour, et al. (2021) considered the artificial intelligence technique and IoT for designing the disease diagnosis model to achieve smart healthcare. The proposed model is utilized for accurate detection of heart and diabetes diseases. The working of model is described using four stages such as data acquisition, preprocessing, classification, and parameter tuning. The different IoT devices are employed to acquire the relevant data. The outlier data are identified using isolation forest technique. The cascade long short-term memory (LSTM) technique is adopted to perform the classification task, while crow search algorithm is applied for tuning the weight and bias parameters of aforementioned technique. The results are evaluated using accuracy, sensitivity, and specificity parameters. It is analyzed that CSO-CLSTM model provides superior results than exiting models in terms of accuracy (96.16), sensitivity (96.38%), and specificity (94.30) rates.

Manogaran, et al. (2021) presented a smart healthcare system based on internet of things environment. The physiological symptoms of patients are collected through wearable devices and in turn, the collected data consists of heterogeneity. Hence, the aim of this work is to present the cognitive data processing technique for uncertainty analysis as well as enhancing the efficiency wearable sensor data management. The aggregation and dissemination uncertainties of sensor data are considered in this work and these are addressed through classification learning. Further, latency and overloaded interval are utilized for evaluating the simulation results and it is analyzed that the proposed cognitive method is more reliable and accurate for handling uncertainty of wearable sensor data.

Su, Ding and Chen (2021) presented the heart disease screening system based on deep learning and internet of things platform. The aim of this study is to measure the irregularities in context of heart and earlier detection of heart disease. This study considers the STM32 as IoMT controller and integrate it to IoT devices such as temperature sensor, pulse sensor, and sphygmomanometer cuff. Further, deep learning method is integrated into aforementioned architecture for detecting the heart irregularities and disease. The experiment results stated that proposed screening system is successfully detected the variation in heart signals.

Hossen, et al. (2022) developed the federated machine learning based model for detecting the skin disease as well as enhancing the security in IoMT environment. This work considers the CNN technique with federated learning for the detection of skin disease. The image augmentation technique is also adopted for enlarging the skin dataset and data privacy concern is addressed through federated learning. Further, the skin disease is divided into four classes such as acne, psoriasis, eczema, and rosacea with the help of dermatologist. The results are evaluated using precision, recall and accuracy. The accuracy rate of the proposed detection model is 81.21%, 86.57%, 91.15%, and 94.15% using 1000, 1500, 2000, and 2500 sample data.

Siddiqui, et al., designed an IoMT and cloud based intelligent prediction model for detection the breast cancer stages. The features are extracted from mammogram images using deep learning technique. The prediction of breast cancer and its stages is accomplished through two sub layer:- (i) Application layer and (ii) performance layer. The CNN technique is employed in application layer to classify the data. While, performance layer consists of parameter such as accuracy, precision, and miss rate. The training accuracy of the proposed model is 98.86%, while the validation accuracy of the model is 97.81%. It is also observed that proposed model considerably reduces the breast cancer mortality rate.

Ahmed, et al. (2021) demonstrated a health monitoring framework to predict and analyze the COVID-19. The proposed framework integrates the IoT platform and big data analytics. The big data analytics is adopted to perform descriptive, diagnostic, predictive, and prescriptive analysis for assessing the several symptoms of pandemic. The diagnosis and prediction task is achieved through neural network based technique. The results stated that neural network model obtains superior accuracy (99%) than other ML models.

Abdellatif, et al. (2021) considered the edge computing and Blockchain for processing the medical data, called MEdge-Chain. The objective of work is to design a health-care system that aggregates the different health attributes under the national healthcare system which can enable swift, secure and storage of medical data. Further, the edge computing provides an automated patient monitoring system in remote manner as well as for critical medical emergence. The latency and computation cost of secure data exchange are handled through Blockchain technologies. It is summarized that proposed MEdge-Chain model is efficient model for data processing and achieved low latency.

Rhayem, et al. (2021) presented the patient monitoring system based on context aware, semantic information and internet of thing environment. The aim of this work is to describe the relationship among heterogeneous medical connected objects and its respective data. Further, SWRL rules are designed to interpret and manage the data into different contexts and these rules are also utilized for diagnosis and prediction of disease. The effectiveness of the monitoring system is evaluated using a case study based on gestational diabetes. The results are assessed using precision, recall and f-measure parameters. It is reported that proposed monitoring system obtains superior results than other models.

Dami and Yahaghizadeh (2021) predicted the cardiovascular event based on deep learning with respect to IoT environment. The deep belief network is utilized for extracting the relevant features from the collected dataset. The collected dataset contains the 5 min electrocardiogram (ECG) recording and demographic data. The time frequency features are extracted from the ECG signals. While, the demographic feature in context to heart is collected through wearable devices. The prediction task is executed using LSTM technique and predictive results are evaluated using various performance parameter, but accuracy is considered as more potential parameter. The performance of LSTM-DBN is compared with MLP, RF, support vector machine (SVM), and LR techniques and it's observed that LSTM-DBM attains 88.42% accuracy rate.

Madhavan, et al. (2021) demonstrated a Res-CovNet framework using IOHT and transfer learning for detection of COVID-19. This work considers the chest X-ray images for detection of COVID-19. The preprocessing task is accomplished through Res-CovNet, and the storage aspect is handled through MangoDB. The efficacy of proposed model is assessed over five thousand eight hundred fifty six images and simulation results are evaluated using accuracy parameter. It is noticed that proposed framework achieves 96.2% of accuracy rate.

Alqaralleh, et al. (2021) integrated the deep learning (DL) technique with Blockchain to design secure image transmission and diagnosis model in IoMT environment. The proposed diagnosis model contains data collection, secure transaction, hash value encryption, and data classification.

The data are collected through smart sensor devices. For the secure transmission, an optimal key is generated using ECC and the combination of grasshopper and fruit fly optimization is utilized for generation of optimal key. The hash encryption is done through NIS with BWT and finally, DBN is considered for diagnosis of disease. The performance of the proposed diagnosis model is validated using specificity, sensitivity and accuracy parameters. It is analyzed that proposed model provides higher specificity (96.73%), sensitivity (97.91%), and accuracy (98.96%) than other compared models.

Aitzaouiat, et al. (2022) presented an intelligent platform based on WBN, IoT, and machine learning to predict the involuntary seizures. WBN and IoT devices are considered for collecting the data form the end users. The prediction task is completed through QuLRA, SeCA, and RT2CA. Moreover, IoT/WEB proxy security mechanism is adopted for secure transmission in between CoAP/DTLS protocol and hospital information system. The performance of proposed platform is evaluated using rand index and accuracy. Authors claimed that proposed platform outperforms than exiting models and techniques in context of secure communication and classification results.

Raju, et al. (2022) developed a smart heart disease prediction system using IoT and Fog computing environments. The proposed prediction system integrates the cascaded deep learning model for predictive task. The patient's data are collected through IoT devices and optimized cascaded deep learning technique is utilized for prediction of heart disease. The hyper parameters of deep learning are optimized through galactic swarm optimization (GSO) technique. The performance of prediction system is evaluated using a set of well-defined performance parameters and it is found proposed heart disease prediction system obtains superior results with most of parameters as compared to similar existing models.

Ali, et al. (2021) designed a health-care monitoring framework to predict the abnormality. The proposed framework integrates the cloud computing and big data analytics to override the issues with traditional monitoring systems. The data analytics are performed using the ontology and Bi-LSTM, while cloud computing is utilized to store the data. Moreover, the dimensionality of data is reduced through information gain technique and aim of this process is to choose relevant features and improve the classification accuracy. The performance of proposed framework is investigated using blood pressure and diabetes prediction. The results showed that proposed framework effectively handles data heterogeneity and also enhances the classification accuracy of blood pressure and diabetes.

Kumar, Mandal and Kumar (2022) demonstrated the fog based framework for accurate prediction of diabetes disease using cloud environment. In this work, patient data are collected with the help of sensor in remote manner. Further, fog computing is utilized to collect and process the data end nodes, and also for immediate communication. The processed data are analyzed on the cloud layer using ANFIS-PSO-WOA technique. The results showed that proposed model achieves more than 92% of accuracy rate than ANN, SVM, and ANFIS.

III. Proposed Model and Description

In present era, IoT and cloud computing having significant impact for several applications. The issues associated with cloud are effectively handled through centralized IoT based platform. These issues are described in terms of lack of scalability and indulge requirements. These emerging technologies are widely adopted to design intelligent frameworks for health-care data analysis, disease diagnosis, surveillance system, precision agriculture, etc. It is observed that large amount of data is generated in healthcare field. To process such massive data, new computing techniques such as edge and fog computing are best when the application requires low delay and energy efficient system. However, issues such as less accuracy and response time are to be considered. However, it is seen that integration of fog, cloud, IoT, and edge computing obtains superior computation, communication, and storage solutions. This integration also superior in terms of n/w bandwidth, privacy, mobility, latency, and security. It is also found that combination of fog and cloud computing can be considered for real time and latency sensitive applications. It is also observed that existing heart disease system suffered with higher response time, workloads, resource usages, and energy consumption. Hence, the target is to have an intelligent DSS for heart disease based on fog computing in combination with IoT. The IoT devices and gadgets are used for collecting the heart disease related data from the patients. Different sensors are assumed for gathering the patient data in terms of activity level, blood pressure, electroencephalography (EEG), oxygen level, electromyography (EMG), respiration rate, and ECG. Further, fog nodes are assumed to process the heart disease data with high computing and less response time, delay, and latency compared to cloud scenario. Moreover, the collected data are transferred through the gateway devices to the worker/broker node for heart disease diagnosis. It is also mentioned that ECG signals are considered to extract the features for diagnosis of the heart disease and these features are separately extracted and processed. The possible features that are extracted for heart disease diagnosis are standard deviation, entropy, heart rate, peak amplitude, zero crossing, skewness, mean, median, kutosis, and energy. Now, Fogbus is come into picture and having significant role for designing the DSS to heart disease diagnosis. Further, the preprocessed data is fed to the DSS and in DSS, deep forest cascading is implemented for the purpose of heart disease diagnosis. The deep forest technique predicts the data either heart disease or without heart disease while DSS will predict heart disease with maximum prediction accuracy. Fig. 2 depicts the proposed DSS for diagnosis of heart disease.

A. System Configuration

The proposed intelligent DSS can be described as light weight fog system that takes heart disease patients information

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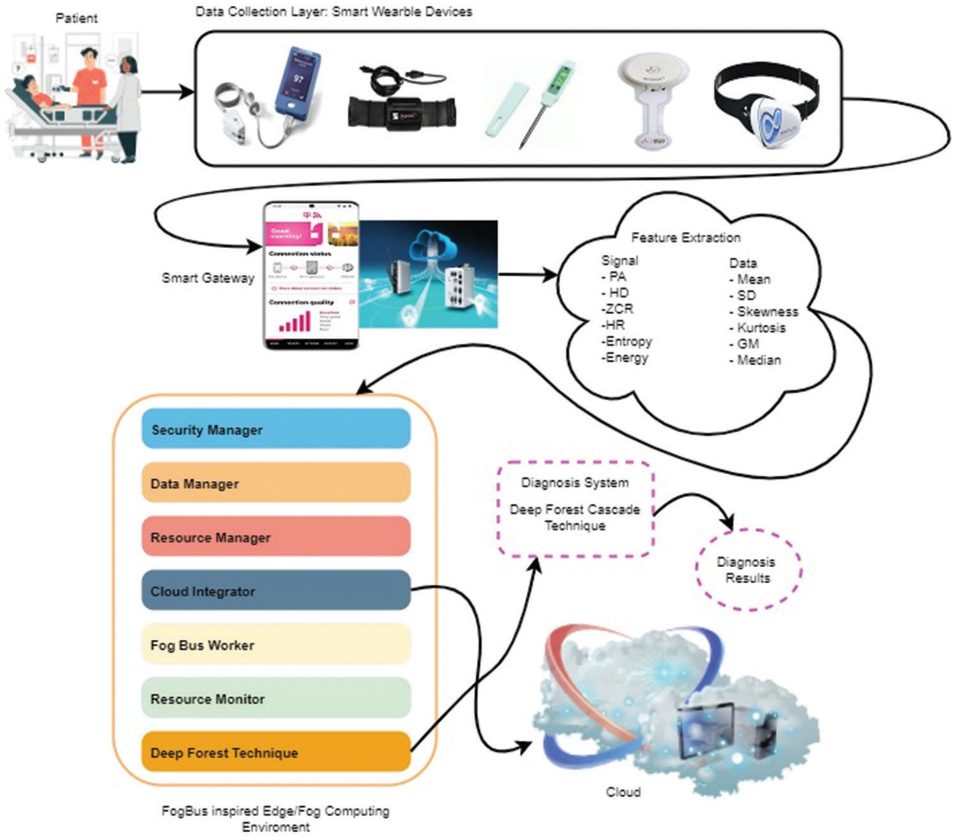

Fig. 2. Demonstrates the proposed decision support system for heart disease diagnosis.

through sensors and smart devices. FogBus is integrated into the proposed DSS and task of FogBus is to diagnosis of heart disease affected patients. Moreover, the Fogbus can be adopted for combining the Fog and cloud environments and it is also deliberated for deployment as well as development. It also provides structured communications and platform independent. The structured communications can be described as dedicated links with sensor devices and smart gadgets and another significance is to send data and task to worker nodes of fog system. While, the broker nodes manage the task initiation and resources. A security manager is also considered to ensure the robustness and dependability of proposed environment through encryption and authentication. Further, FogBus considers the HTTP RESTful APIs to integrate and communicate with the cloud layer.

B. IoT

The proposed intelligent DSS integrates several hardware devices (sensors and smart gadgets) and application software for smooth communication and integration of edge, fog, and cloud to obtain superior results. The proposed DSS contains environmental sensor, medical sensors and activity sensors as hardware devices. Few of sensors are described as ECG sensors, EEG sensors, glucose level sensors, EMG sensors, temperature sensors, respiration rate sensors, oxygen level sensors, and EMG sensors. The data regarding the patient health are collected through aforementioned sensors and collected data are transmitted through connected devices.

Data collection

The working of proposed DSS is tested on gathered data. This data are collected through different internet medical of things devices. These are the smart gadgets that are connected with patients to get the desired data. The details of the aforementioned medical sensors are listed as below.

- Glucose Sensor: This sensor measures the blood glucose level of the patients and can be significant one to manage the diabetes as monitoring of the glucose level is one of crucial activity to predict the heart disease. It is noticed that people with diabetes having higher chance for developing heart disease rather than people without diabetes.
- Respiration Sensor: The respiration sensor can be described through standard pulse oximeters and can be adopted for monitoring of respiratory rate. The outcome of respiration sensor can be defined in terms of flow rate in hundred per minute and it is important parameter to compute heart rate variability.
- Temperature sensor: Used to determine patient body temperature. The increased sensed temperature can also increase the heart beat rate. Hence, it is important to measure the temperature for diagnosis of heart disease.
- Oximeter: Used to measure the oxygen level in blood. Decrement in oxygen saturation level is related to faster heart rate and in turn variability in plus rate.
- EMG Sensor: It is used to evaluate and record the electrical signal resulted by skeletal muscles and adopted in clinical and biomedical applications. This sensor also determines

relationship among nerve cells and muscles in terms of health status. The range of the EMG signal is in between 0.1 and 0.5 mV.

- EEG Sensor: This sensor records the electrical signals of the brain. It is described in terms of waveform which reflects the cortical electrical activity.
- ECG Sensors: This sensor is utilized to determine the relationship among heart rate and rhythm.

Feature extraction

In this work, features are extracted from the signal as well as collected data for accurate prediction and diagnosis of heart disease.

Feature extraction form signal

This subsection presents the features that are extracted from the ECG signals for the purpose of heart disease diagnosis. Signals fed to feature extraction phase. In turn, several features are extracted which are listed in Table I. Through this process, redundant data is also reduced from the dataset and prediction process becomes more generalized.

Feature extraction form data

This subsection discusses the spectral features that are also extracted from the collected data for effective prediction and diagnosis of heart disease. These features are defined as mean, median, G-mean, standard deviation (SD), skewness, and kurtosis. The aim of these features is to minimize the resources for processing of data without loss of relevant information. Further, the problem of over fitting of data is also resolved. Table II shows the spectral features extracted for heart disease.

C. Fog Computing

This subsection discusses the working of the fog nodes. In this work, the IoT devices can be severed as fog devices. These nodes process the collected data. It is conveyed that fog computing is implemented through FogBus and it contains several nodes such as worker, broker, and cloud data centers. The broker nodes receive the collected data from the gateway devices. It is also stated that prior to send the data, gateway devices send the job requests to the input module and the security module is responsible to transfer the data with secure communication to avoid data tempering and unauthorized access. In turn, system credibility and integrity can be improved. Further, it is said that arbitration module is one of the significant element of the resource scheduling especially the broker that computes the status of the load at the worker side in terms of input. It also identifies the subset of nodes that can perform the real time task. Moreover, the task can be allocated by worker node with the help of resource manager of broker node. However, these nodes can be characterized as stand-alone system and embedded devices that consist of deep forest cascading technique to analyze and process the input data and obtain the results. The main functions of worker node are summarized as filtering, preprocessing, data storage and analytics. To accomplish aforementioned task, data could be taken by the worker

TABLE I
Description of the Features Extracted from Signal Data

Features	Description
Peak amplitude	Max. positive\negative deviation from zero reference level
Harmonic distortion (HD)	$\frac{\sqrt{\sum_{v=2}^{N/2} h_v^2}}{h_1}$ (1)
Heart rate	Computed using interval for two successive QRS
Zero-crossing rate	$Zc_n = \sum_{t=-\infty}^{\infty} \left\| sgn\left[y(t) - sgn\left[y(t-1)\right]\right] \right\| ws(n-t)$ $ws(n) = \begin{cases} \frac{1}{2N} 0 \le n \le N-1, \\ 0\, otherwise \end{cases}$ $sgn\left[y(t)\right] = \begin{cases} 1\, y(t) \ge 0 \\ -1\, y(t) < 0 \end{cases}$ (2)
Entropy	$e = p_i log p_i$ (3)
Standard deviation	$\sigma^2 = \frac{1}{N}\sum_{j=0}^{N-1}\left(y_j - \mu\right)^2$ (4)
Energy	$En = \int_{-\infty}^{\infty} \left\|y(t)\right\|^2 dt$ (5)

TABLE II
Illustrates the Spectral Features

Features	Description
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} P_i$, N denotes the total pixels presented in segmented region.
Median	$Med(P) = \begin{cases} P\left(\frac{N}{2}\right) if, N\, is\, even \\ \left(P\left(\frac{N-1}{2}\right) + P\left(\frac{N+1}{2}\right)\right) if, N\, is\, odd \end{cases}$ (6)
G-mean	$GM = \left(\prod_{i=1}^{N} P_i\right)^N = \sqrt[n]{P_1, P_2, P_3, \ldots, P_N}$ (7)
SD	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_i - \mu\right)^2}$ (8)
Skewness	$sk = \left(\frac{1}{N \times \sigma^3} \times \sum_{i=1}^{N}\left(p_i - \mu\right)^3\right)^{1/3}$ (9)
Kurtosis	$ku = \left(\frac{1}{N \times \sigma^4} \times \sum_{i=1}^{N}\left(p_i - \mu\right)^4\right)^{1/4}$ (10)

SD: Standard deviation

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node from gateway nodes. The third part of the proposed DSS is cloud layer. It can be effectively used for processing of data and storage. If, size of data is higher than average, then latency can be increased and in turn fog layer will be overloaded. Hence, it is suggested that relevant features can be extracted from the data using efficient feature extraction algorithm and final decision can be taken on the basis of relevant features. The resource-manger consists of two main elements: Workload and arbitration module. Workload manager is designed to handle and process huge data. While arbitration module is responsible to schedule the fog and cloud resources as well as queued tasks processing and this module is integrated within broker node.

D. Deep Forest Cascade Technique

Finally, deep forest cascade technique is employed on the extracted dataset to obtain the desired outcome for prediction of heart disease. The prediction task is accomplished through resource manager as it is responsible to receive the data from gateway devices and task distribution to fog nodes. The final outcome can be recognized either heart disease or not. The deep forest is a new ensemble technique which consists of cascade structure. It is also reported that cascade structure contains more appropriate features than other techniques (Zhou and Feng, 2019) (Zhou and Feng, 2017). Further, it is two-step process:- (i) Multi-grained scanning and (ii) cascade forest. The high dimensional features are extracted using multi grained scanning while classification and prediction task are completed through cascade structure and it contains several forests with multiple trees. The selection of root node is done through Gini index method and it is calculated for each feature. Further, these features are arranged according the Gini index value and feature with lowest Gini index become root node. Final, tree is created on the basis of Gini Index. The computational procedure for computing the respective class of data is mentioned in Fig. 3.

Both scanning and cascade structure are utilized in this work. The relevant feature for classification are chosen using scanning procedure, while classification and prediction task is conducted using cascade structure. The cascade structure contains four forest with four random tree and further, fifty trees are considered in each forest. The parameters values are taken same as presented in (Kumar, Mandal and Kumar, 2022) (Zhou and Feng, 2019). The working of cascade structure is demonstrated in Fig. 4. The features are given

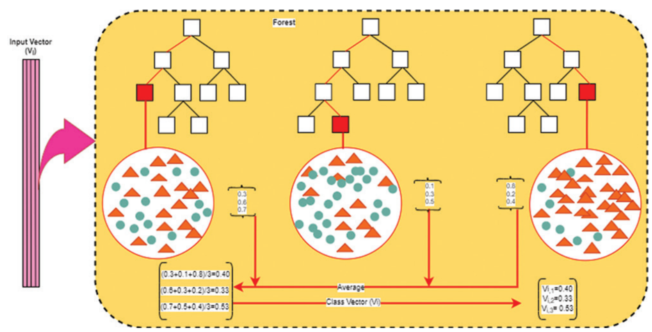

Fig. 3. Computational procedure for computing the class of data.

as input to cascade structure and input features are parsed through cascade structure. This parsed input is moved from 1st level to nth level. At each level, parsed input (previous output) is integrated with input data to produce optimal solutions. This process is continuing until cannot reach nth level. The class label is determined using the nth level. It is also seen that deep forest occurs less sensitivity to input parameters. The computational procedure of deep forest is listed in Algorithm 1.

IV. Experimental Results

The suggested system is implemented in Python environment Intel core-i7 processor, RAM 8 GB, and 64-bit Windows OS. The different scenarios such as training-testing and cross validation are considered for evaluating the system. Simulation results of the suggested system are compared with recurrent neural network (RNN) (Choi, et al., 2017), CNN (Maragatham and Devi, 2019), LSTM (Dutta, et al., 2020), SVM (Ayon, Islam and Hossain, 2020), NN (Balakrishnan and Kumar, 2021), and RT (Balakrishnan and Kumar, 2021).

A. Performance Analysis and Discussion

The results are evaluated using the four different evaluation methods such as training-testing (70–30%), training-testing (80–20%), 5 cross-fold evaluation method, and 10 cross-fold evaluation method. Table I shows the experimental results according to accuracy and F1-score. It is clearly indicated

Algorithm 1: Proposed Deep Forest Technique

Input: Heart Disease Dataset (DA), No. of Level (LE), No. of Forests (FO), Number of trees (TN).
Output: Either Heart Disease or Not Heart Disease

1. Initialize no. of forests, No. of trees (TN), No. of dimension in dataset (DIM), training data (TR) and In_Res.=0;
2. For i=1 to LE, do following/Start Training Phase
3. For j=1 to TR, do following
4. For k=1 to FO, do following
5. Construct decision tree for TR using DIM relevant features of heart disease (DA) and Init_Res.
6. Pick the optimal spilt node based on Gini Index.
7. Design tree at depth level (d).
8. Create TN number of tree for forest.
9. Endfor
10. Endfor
11. Endfor
12. For i=1 to L, do following/Start Testing Phase
13. For j=1 to N, do following
14. For k=1 to F, do following
15. Create decision tree for test data based on DIM relevant features using heart dataset (DA) and Init_Res.
16. Pick optimal spilt node based on Gini Index.
17. Design tree at depth level (d).
18. Construct TN number of tree for forest.
19. Endfor
20. Endfor
21. Endfor
22. Evaluate the class of heart data based on ensemble of decision trees.
23. Compute the efficiency of algorithm using performance parameters

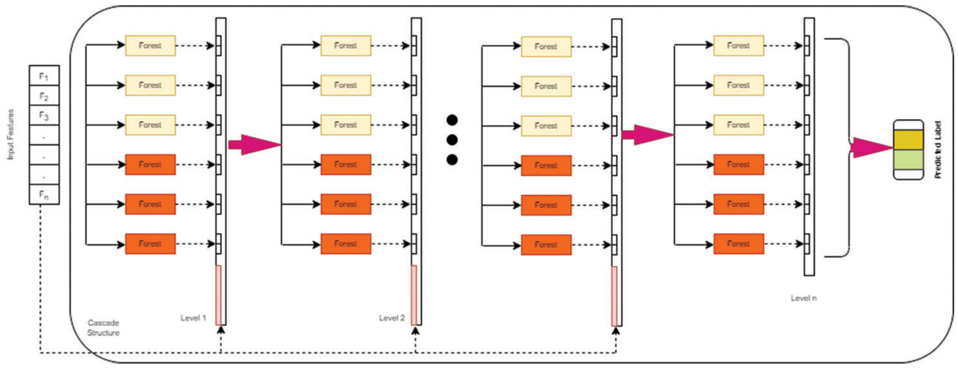

Fig. 4. Cascade forest structure using four forest.

that the suggested system has superior accuracy (95.64%) and F1-score (96.95%) rates using 10 cross fold method when compared to other schemes. Similarly, it is noticed that ANN exhibits less accurate results, that is, 88.08% and 91.92%, among all other techniques. On the analysis of evaluation methods, it is observed that 10-cross fold method having advantage over training-testing (70–30%), training-testing (80–20%), and 5 cross fold evaluation method. The results showed that proposed DSS achieves 95.64% and 96.95% of accuracy and F1-score rates, while F1-score accuracy rates with training-testing were (70–30%), training-testing (80–20%), and 5 cross fold evaluation method are (90.45% and 91.56%), (92.56% and 93.21), and (94.17 and 94.53), respectively. Similar, in case of ANN, the best performance is achieved using 10 cross fold method, that is, 88.08% (accuracy) and 91.92% (F1-score), while, the performance with training-testing (70–30%), training-testing (80–20%), and 5 cross fold evaluation method are (82.64% and 84.37%), (86.05% and 88.11%), and (87.15% and 90.46%). Hence, it is summarized that 10 cross fold validation method is significant evaluation method for the suggested system. The proposed DSS and other techniques obtain less accurate with training-testing (70–30%) method for diagnosis pf heart disease. However, proposed DSS also obtains better results than other techniques for heart disease diagnosis with training-testing (70–30%) evaluation method.

Table II shows the specificity and sensitivity results of the suggested model. It is analyzed that proposed DSS attains better sensitivity, that is, 96.39% and specificity, that is, 97.52% in comparison to other techniques. While, the performance of ANN technique is not so good in terms of sensitivity (92.24%) and specificity (91.60%) as compared other techniques like RT, SVM, RNN, LSTM and CNN. On analyzing the evaluation methods, it is found that 10 cross-fold technique improve the efficiency of the suggested system when compared to training-testing (70–30%), training-testing (80–20%), and 5 cross fold evaluation methods. While, training-testing (70–30%) method exhibits lower performance among all four evaluation methods. Similarly, it is noticed that ANN exhibits less accurate results i.e. 88.08% and 91.92%, among all other techniques. In addition, it is noticed that 10 cross-fold technique has superiority over training-testing (70–30%), training-testing (80–20%), and 5 cross fold evaluation method. The results showed that proposed DSS provides 96.39% and 97.52% of sensitivity and specificity rates. Other side, training-testing (70–30%), training-testing (80–20%), and 5 cross fold evaluation method achieves (91.27% and 92.14%), (93.08% and 93.87%), and (94.56% and 95.31%) sensitivity and specificity rates using proposed DSS for heart disease diagnosis. Similarly, ANN obtains the best results using 10 cross fold method, that is, 92.24% of sensitivity and 91.60% of specificity rate, while with training-testing (70–30%), training-testing (80–20%), and 5 cross fold evaluation method ANN achieve (83.91% and 84.67%), (87.76% and 88.91%), and (89.29% and 90.17%) of specificity and sensitivity rates. It is shown that the suggested system hit significantly superior results than all other techniques using all aforementioned evaluation methods. Other side, ANN technique having less accurate results for diagnosis of heart disease using all evaluation methods. It is also noted that among all evaluation methods, training-testing (70–30%) method obtains less accurate results using all techniques.

Fig. 5 demonstrates the comparative analysis of accuracy parameter of proposed DSS and other techniques using all evaluation methods such as training-testing (70–30%), training-testing (80–20%), 5 cross-fold, and 10 cross-fold. The suggested system has higher accuracy rate using all evaluation methods and predicts the heart disease more accurately than other models. In addition, it was noticed that ANN having less accuracy rate among all techniques including proposed DSS for diagnosis of heart disease. In deep learning variants RNN, LSTM, and CNN, the CNN model achieves higher accuracy rate among all and also outperform than rest of techniques except proposed DSS.

Table III shows the DSS system accuracy simulation results when they are compared to other techniques while Table IV shows the simulation results of specificity and sensitivity of the proposed DSS system and other existing models for heart disease prediction. F1-score and sensitivity results of proposed DSS and other techniques for diagnosis of heart disease are reported into Figs. 6 to 8 using all evaluation methods. Fig. 6 shows that the suggested system having higher F1-score when compared to other models, while ANN technique having lower F1-score rate among all techniques using all evaluation model. In addition, the

TABLE III
The DSS System Accuracy Simulation Results Compared to other Techniques

Techniques	Training-Testing (70–30%)		Training-Testing (80–20%)		5 Cross Fold Validation		10 Cross Fold Validation	
	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score
ANN	82.64	84.37	86.05	88.11	87.15	90.46	88.08	91.92
RT	84.51	85.57	87.34	88.53	88.41	91.23	89.44	92.73
SVM	85.74	87.58	88.2	89.24	89.54	92.11	90.34	93.34
RNN	86.93	87.95	89.41	90.76	90.83	92.76	91.58	94.17
LSTM	88.11	90.34	90.67	91.03	92.33	93.67	93.22	95.33
CNN	88.34	91.26	91.07	91.75	93.24	94.01	94.68	96.32
Proposed DSS	90.45	91.56	92.56	93.21	94.17	94.53	95.64	96.95

ANN: Artificial neural network, SVM: Support vector machine, RNN: Recurrent neural network, LSTM: Long short-term memory, CNN: Convolutional neural network, DSS: Decision support system

TABLE IV
Simulation Results of Specificity and Sensitivity Proposed DSS and other Exiting Models/Techniques for Heart Disease Prediction

Techniques	Training-Testing (70–30%)		Training-Testing (80–20%)		5 Cross fold validation		10 Cross fold validation	
	Sens.	Spec.	Sens.	Spec.	Sens.	Spec.	Sens.	Spec.
ANN	83.91	84.67	87.76	88.91	89.79	90.17	92.24	91.6
RT	84.98	86.32	88.01	88.96	89.63	90.74	91.81	93.68
SVM	87.14	88.23	88.79	89.91	90.81	91.06	92.24	94.46
RNN	87.36	88.21	90.48	91.11	91.54	91.84	92.97	95.41
LSTM	89.71	91.02	91.53	91.89	92.78	93.12	94.8	95.86
CNN	90.08	91.77	91.38	92.54	93.41	94.04	95.8	96.84
Proposed DSS	91.27	92.14	93.08	93.87	94.56	95.31	96.39	97.52

ANN: Artificial neural network, SVM: Support vector machine, RNN: Recurrent neural network, LSTM: Long short-term memory, CNN: Convolutional neural network, DSS: Decision support system

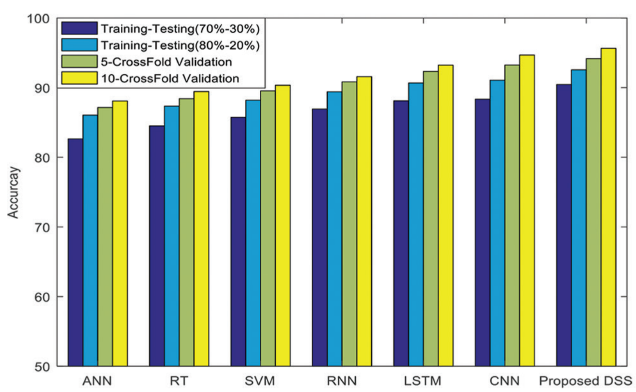

Fig. 5. Comparative analysis of different evaluation methods using accuracy parameter.

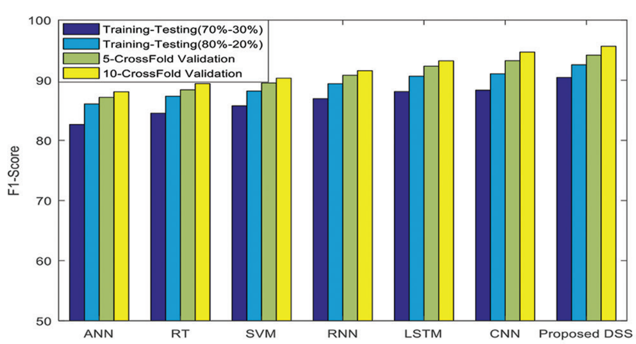

Fig. 6. Comparative analysis of different evaluation methods using F1-score parameter.

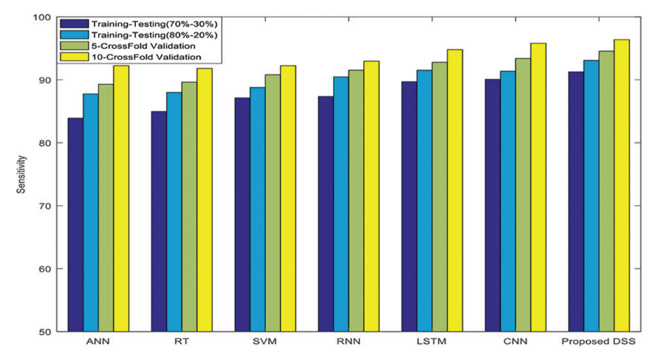

Fig. 7. Comparative analysis of different evaluation methods using sensitivity parameter.

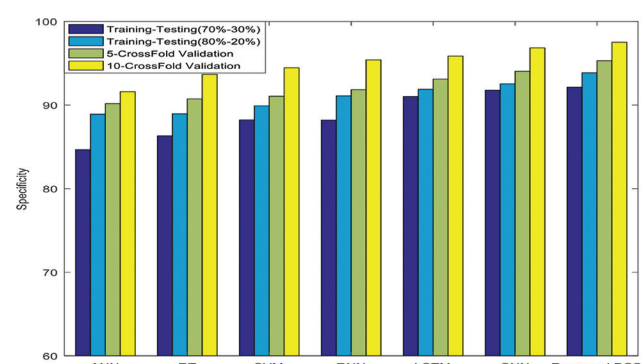

Fig. 8. Comparative analysis of different evaluation methods using specificity parameter.

10-cross evaluation produces considerably better outputs with all techniques including proposed DSS for heart disease diagnosis. Fig. 8 shows the sensitivity results of the suggested system. Again, proposed DSS achieves superior

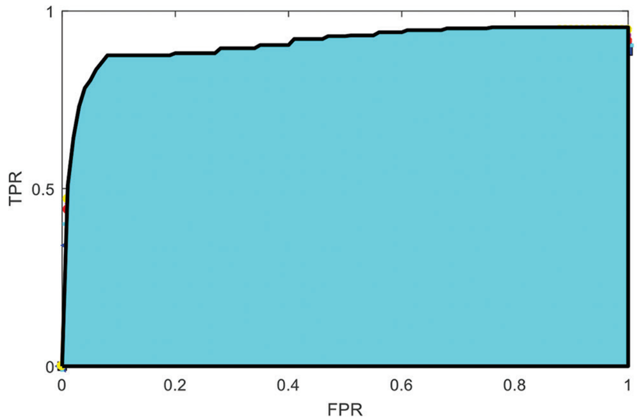

Fig. 9. The area under the curve results proposed decision support system for prediction of heart disease.

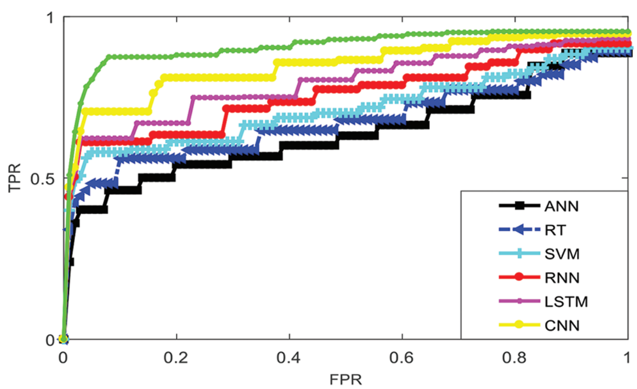

Fig. 10. The area under the curve results proposed decision support system and other existing techniques/models.

results for heart disease diagnosis than other techniques using all evaluation methods. It is also observed that RT technique having less accurate sensitive\ results using 5 cross fold and 10 cross fold evaluation methods, while ANN provides lower sensitivity results using training-testing (70–30%) and training-testing (80–20%) evaluation methods. Fig. 8 illustrates the specificity results of the proposed DSS and other technique using all evaluation methods. It is analyzed that proposed DSS outperforms than other techniques and provides higher specificity with each evaluation method. Other side, ANN shows less accurate performance in terms of specificity rate among rest of techniques using each evaluation. In addition, the 10 cross-fold evaluation is significant for evaluating the performance of the proposed DSS and other techniques. It is also observed that the performance of all techniques is substantially enhanced using 10 cross-fold method as compared to training-testing (70–30%), training-testing (80–20%) and 5 cross fold method.

Area under the curve (AUC) is also an important parameter for predicting the performance of the newly proposed models for diagnosis of diseases. This work also considers the AUC parameter for the evaluating purpose. AUC results of the proposed DSS are illustrated into Fig. 9. The AUC parameter result is described through relationship between TPR and FPR. The suggested model obtains significant AUC results in earlier iterations. Fig. 10 demonstrates the AUC results compared to other models. The suggested system obtains superior AUC values compared to all other models. It is also stated that proposed DSS converges on optimized AUC results in earlier iteration than other techniques.

V. Conclusion

The proposed DSS is the combination of IMOT, edge, fog, and cloud computing technologies. Data are collected through different IMOT devices regarding the health status of heart. The signal data are also collected to evaluate the condition of heart and different features such as harmonic distortion, entropy, peak amplitude, SD, and heart rate are extracted from the signal data. Apart from above, some features such as mean, median, G-mean, SD, skewness, and kurtosis are also considered from the collected for accurate diagnosis of heart disease. Finally, data are fed to deep forest cascade structure for the purpose of heart disease prediction. In turn, the efficacy of the suggested system is evaluated using F1-score, accuracy, specificity, sensitivity, and AUC parameters. Further, different evaluation methods such as training-testing (70–30%), training-testing (80–20%), 5 cross-fold, and 10 cross-fold are utilized for the purpose of evaluating. Intensive experiments were conducted for the purpose of evaluation, the results was that the suggested system showed superiority in terms of the all above-mentioned parameters. AUC parameter is used for evaluation too, the suggested system having better AUC than RT, SVM, ANN, LSTM, RNN, and CNN. It is observed that proposed DSS with 10 cross-fold validation obtains higher accurate results than training testing (70–30%), training-testing (80–20%), and 5 cross fold method. Hence, it can be concluded that proposed DSS with IoMT, cloud, edge, and fog computing attains considerably better performance than existing models. In future, the proposed system can integrate feature selection techniques, learning strategy, and meta-heuristic algorithm for better classification and predictive accuracy for heart disease diagnosis.

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