International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I8P204
Volume 71 Issue 8, 39-47, August 2023

Original Article

A Fog-Enabled Framework for Ensemble Machine Learning-Based Real-Time Heart Patient Diagnosis

Mohammed S Atoum[1], Abhilash Pati[2], Manoranjan Parhi[3], Binod Kumar Pattanayak[2], Ahmad Khader Habboush[4], Mohammad Alnabhan[5], Emad Qalaja[6]

[1]*Department of Computer Science, University of Jordan, Amman, Jordan.*
[2]*Department of Computer Science and Engineering, Siksha 'O' Anusandhan University, Bhubaneswar, Odisha, India.*
[3]*Centre for Data Science, Siksha 'O' Anusandhan University, Bhubaneswar, Odisha, India.*
[4]*Department of Computer Science, Faculty of Information Technology, Jerash University, Jerash, Jordan.*
[5]*Department of Computer Science, Princess Sumaya University for Technology, Amman, Jordan.*
[6]*Department of Computer Science, Mutah University, Karak, Jordan.*

[1]*Corresponding Author : m.atoum@ju.edu.jo*

Received: 03 May 2023 Revised: 20 June 2023 Accepted: 17 July 2023 Published: 15 August 2023

Abstract - *Accurately forecasting human diseases continues to be a challenging issue in the search for better and more crucial studies. Heart disease is a potentially deadly condition that affects individuals everywhere. With the use of data fusion techniques and adaptive machine learning (ML) methods on diverse medical management datasets, the Internet of Medical Things (IoMT) plays a crucial role. A healthcare monitoring suggestion system accurately identifies and proposes heart patient issues. Various machine-learning approaches and algorithms for predicting cardiac disorders have recently been created. Many systems cannot handle the massive volume of multi-feature raw data on cardiac disorders. In this work, the two datasets on heart diseases from the UCI-ML warehouse, namely, Cleveland and Hungarian, are considered and then fused into a single dataset along with five basic ML classifiers. The suggested approach attained the maximum level of accuracy considering stacking as an ensemble classifier on these five ML approaches, particularly on the fused dataset, against these five classifiers. The experiments' accuracy, precision, sensitivity, specificity, f-measure, and MCC reached 82.39%, 85.86%, 83.33%, 81.08%, 84.58%, and 64.09%, which are comparatively higher. This study uses Fog computing ideas and can remotely diagnose cardiac patients instantly in low latency, minimum energy consumption, etc., as from the experiments*.

Keywords - *Fog computing, IoMT, Ensemble learning, Machine Learning, Heart Diseases Diagnosis.*

1. Introduction

Recent advances in high-performance computers and cutting-edge biotechnology have been directed towards optimizing the efficiency and cost-effectiveness of disease diagnosis and online healthcare survey techniques. Efficiency and reliability necessitate precise model creation from massive amounts of e-healthcare data. Several different things can cause heart disease. The majority of the world's 422 million heart disease sufferers live in poor and medium-income nations, where the condition is responsible for 1.5 million deaths annually [1-2].

One of the most pressing issues with Cloud-based infrastructure today is the synchronization of data before cutover and data transfer. The necessity for a centralized IoMT-based infrastructure has limited scalability because of Cloud computing security issues. Health systems, such as health monitoring and other systems, become sensitive to device latency as more and more data is collected. Fog computing enhances Cloud computing by making better use of adjacent, yet still essential, resources. The current models for Fog computing exaggerate the response time or result accuracy, and the technology management causes compatibility issues. Intelligent devices are on the rise in many sectors of society, from food and agriculture to medicine, in the age of digital technology. Massive volumes of data generated by sensors in IoT-enabled devices are sent over Fog or Cloud computing to data centers housing deep learning algorithms. The viability of an Internet-based economy depends on developing Fog computing standards, including Cloud computing. Both the professional and academic communities have invested much in these two areas. Cloud computing is not a viable option for real-time feedback applications due to the significant lag in response time. The speed and responsiveness of big data processing using IoT, Fog computing, and Edge computing are crucial for monitored target applications. Fog computing synchronizes latency and continuous applications thanks to its huge store capacity, dependable processing and communication methods, and low-scale latency and network bandwidth. Mobility, security, and safety are all enhanced by edge devices. Application standards are developed with input from several Cloud components, including big data systems, IoT devices, Fog and Edge computing, and others. To reduce power consumption, network idleness, and network reaction time, fog computing makes use of routers, switches, nodes, and gateways [3,21].

Ensemble learning (EL), an advancement in machine learning (ML), can boost the precision and effectiveness of predictive analyses. The goal of this study is to provide a paradigm for a smart real-time decision support system that can increase diagnostic accuracy while dealing with complex data. The remote detection of cardiovascular disease is made possible by suitable analysis and IoMT. This proposed Fog-enabled Cloud computing architecture is evaluated using FogBus in terms of several performance and network parameters.

These are a few of the study paper's significant contributions:

- Provide a general framework for Fog computing ensemble machine learning (EML).
- Using an EML technique, a lightweight computing technique for diagnosing cardiac patients was developed.
- Integrating IoT-Edge-Cloud with this system allows for real-time data processing.
- The implementation of this proposed work involves looking into different network and performance parameters.

The paper proceeds as follows: Section 2 details the previous research in this area. The proposed method is covered in Section 3, which also discusses the most recent advances in detecting heart diseases and covers database selection, data pre-processing, and data amalgamation. The obtained results and related discussions are in Section 4. Section 5 covers concluding remarks and subsequent scope.

2. Related Works

Paul et al. suggested Fog computing to monitor patients with chronic conditions swiftly. Limiting context-sensitive data collection to patient health-related information is tough. In this circumstance, a simple sensor-to-Cloud design will not work. System efficiency is boosted because a data center failure is no longer a worry, and fewer data must be exchanged between the Cloud and sensors. They also looked into Fog computing deployment and security [5]. Tuli et al. introduced HealthFog, a framework for merging ensemble deep learning with Edge computing devices, to analyze cardiac conditions independently. By utilizing the IoT, HealthFog provides cardiac patient data as a Fog service. The power usage, jitter, network bandwidth, latency, accuracy, and execution time of the suggested model are all measured by FogBus, a Fog-enabled Cloud framework. Depending on the user's requirements, HealthFog can be adjusted to maximize either prediction precision or quality of service [6]. The Blockchain-based, secure healthcare service provided by Shynu et al. in Fog computing. Diabetes and cardiovascular disease are taken into account in the forecasting. To begin, Fog nodes collect and record patients' medical records on a distributed ledger. Rule-based clustering is used to classify patients' medical records initially.

At last, the authors use adaptive neuro-fuzzy inference (FS-ANFIS) to foresee CVD and diabetes. The suggested action was assessed through extensive experimentation and study utilizing real-world healthcare data. The effectiveness of rule-based clustering is measured in terms of purity and NMI. According to the results of the experiments, the proposed theory accurately predicts illness. The proposed method is 81% more effective than prior neural network techniques [7]. Information from the BSN and the Fog was combined by Shakya and Joby. High-quality data is gathered from routine activities thanks to sensors. An ensemble classifier is trained using the information to identify cardiac conditions at an early stage. In a Fog computing setup, data is gathered with the help of decentralized processing. The data from the many nodes is aggregated in a central database used in Fog computing. The quality of categorization is enhanced with a new kernel random data collector. 96% accuracy was achieved in an experiment using 10 depths, 45 estimators, and 7 feature parameters [8]. Raju et al. introduced a paradigm that uses a hybrid of Edge, Fog, and Cloud computing to transfer data swiftly. Data about patients is gathered using hardware.

Signals are analyzed to identify significant characteristics of the heart. Information for feature extraction from a further characteristic is gathered. The diagnostic system (CCNN) receives all these characteristics via a more advanced cascaded convolution neural network. Here, GSO (GSO) is used for optimizing the CCNN's hyperparameters. GSO-CCNN outperforms PSO-CCNN, GWO-CCNN, WOA-CCNN, DHOA-CCNN, DNN, RNN, LSTM, CNN, and CCNN in terms of accuracy, as shown by the performance study. The effectiveness of the suggested approach is confirmed by comparison to existing models [9]. Verma et al. created FETCH, a system that facilitates communication with edge computing devices to improve deep learning tools and automate monitoring. It provides a firm foundation for healthcare delivery in the real world, including treating heart disease and other illnesses. FogBus is used in the Fog-enabled Cloud computing architecture, and it provides benefits in areas including efficiency, speed, reliability, and robustness [22]. Golkar et al.'s innovative performance model was made possible by incorporating Fog computing, priority queues, and confidence theory with Edge computing hardware. Clinical decision support system (CDSS) data on patients with heart disease was used to verify the model. Using this criterion, the authors assign a CF to each symptom associated with heart disease. The patient's condition is evaluated using CF values from the Fog layer when one or more symptoms are abnormal. Queries are prioritized in Fog-layer queues before they enter the system. Network utilization, latency, and query response time are all reduced by 25.55, 42.92, and 34.28 percent compared to the Cloud model. QoS and response times are improved by prioritizing patient requests based on CF values in the CDSS [11].

3. Proposed Work

The datasets and the methodologies employed in this suggested work are briefly discussed in this section. This section also focuses on the proposed methodology with the architecture of the flow of communications based on the simulation tool, FogBus.

3.1. Dataset(s) Description

The Cleveland HDD (CHDD), Hungarian HDD (HHDD), and Fused HDD (FHDD), which combines CHDD and HHDD, are the heart disease datasets (HDDs) used in this study to train the model. These datasets were obtained from the UCI-ML warehouse and contained a total of 76 attributes, of which 14 attributes are used to train the model [12]. Table 1 provides a summary of the HDDs that were utilized, whereas the samples of the fused dataset with the 14 attributes considered in this work are depicted in Table 2, where "num" is the class variable. To make binary classifications, the num value 0 is taken as 0, i.e. person without heart disease, and all other values are taken as 1, i.e. person with heart disease.

3.2. Methodologies

This work makes use of FogBus [13]. It is a framework that combines the ideas of IoT, CC, and FC. To guarantee communications' security, privacy, data integrity, etc., it makes use of the blockchain concept. Aneka is a Cloud computing platform that offers developers a simple API implementation. Its main part is made with a service-oriented design in mind. In this work, Cloud resources are used by Aneka, while Fog resources are exploited by FogBus along with Amazon Web Services (AWS) as the Cloud service provider.

Table 1. Short description of the datasets used

Dataset(s)	Number of Instances	Number of Features
CHDD	303	76 (14 considered to train the EML model)
HHDD	297	
FHDD	597	

This work uses several classifiers [15,16,23]. Averaging in a random forest (RF) meta-estimator improves accuracy and reduces overfitting. It applies decision tree classifiers on dataset subsamples. Naive Bayes (NB) classifiers are used for classification challenges. Bayes theorem underpins the classifier. The new instance is put in the category most similar to the existing categories using the k-nearest neighbors (KNN) technique, which assumes that the new example and the prior cases are comparable. Classifying objects by arranging them in a "forest" of de-correlated decision trees is the goal of the Extra Trees (ET) Classifier, a type of ensemble learning method also known as the Extremely Randomised Trees Classifier. A popular supervised learning example for Classification and Regression issues is the Support Vector Machine (SVM). Internal nodes in a decision tree (DT) classifier represent the dataset's attributes, branches stand for decision-making procedures, and leaf nodes indicate the outcomes. These classifiers are ensembled using a stacked classifier to improve these obtained results. The final prediction is calculated by stacking each estimator's output and using a classifier. Stacking uses each estimator's strengths as input to a final estimator. These classifiers educate the dataset to insert the right EML classifier into the nodes.

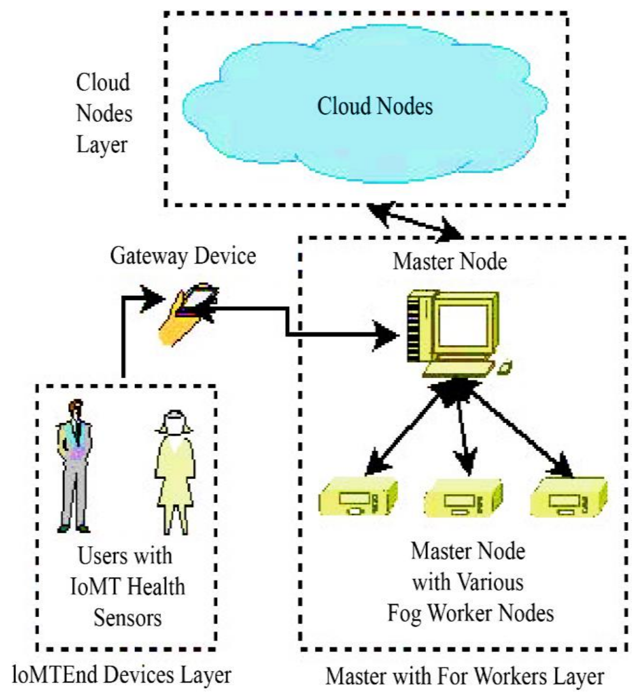

Fig. 1 Proposed work architectural block diagram

Table 2. Samples that were taken from FHDD

Age	sex	Cp	trestbps	Chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	num
43	1	4	150	247	0	0	171	0	1.5	1	0	3	0
40	1	4	110	167	0	2	114	1	2	2	0	7	1
69	0	1	140	239	0	0	151	0	1.8	1	2	3	0
60	1	4	117	230	1	0	160	1	1.4	1	2	7	1
64	1	3	140	335	0	0	158	0	0	1	0	3	1

3.3. Working Principle of Proposed Work

There are basically three layers are presented, as shown in Fig 1, to describe this proposed work, namely, the IoMT End Devices Layer, the Master with Fog Workers Layer, and the Cloud Nodes Layer that constitute the integration concepts of IoT with Cloud and Fog computing.

In the first layer, various IoMT health sensors are used to collect data from the users. These collected data are then sent to the Master node using various gateway devices, smartphones, etc. In the next step, the Master node finds itself whether it is free to process the job requested or else transfer to the connected Fog worker nodes for possible evaluations. If it is noticed as non-availability of the resources, it forwards the requests to the Cloud nodes, acting as a gateway device. The various hardware components employed in this work include the data manager, used to collect the data; resource finder, used to find the available resources, security manager, used for security and privacy verifications, Cloud connector, for connecting Cloud nodes to the Master node, EML Module, for possible evaluations based on the data provided, etc. The detailed working procedure can be found in Algorithm 1, and the flow of the communications in this proposed work is given in Fig. 2.

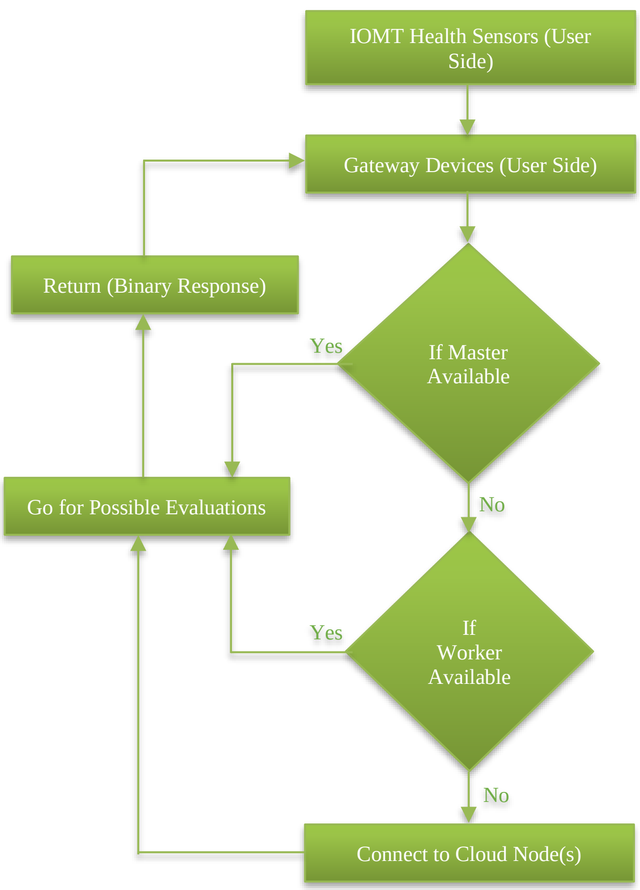

Fig. 2 Flow of communications of the proposed architecture

Algorithm
Input: User Data.
Output: Results Obtained
Step-1: Collect the data from users using various IoMT Health Sensors;
Step-2: Forward these collected data to the Master node using Gateways;
Step-3: If (Master Node Available)
Step-4: Go for possible evaluations and Return Results to Gateways;
Step-5: Else If (Fog Worker Nodes Available)
Step-6: Forward to Fog Worker Nodes;
Step-7: Go for possible evaluations and Return Results to Gateways;
Step-8: Else
Step-9: Forward to Cloud Nodes;
Step-10: Go for possible evaluations and Return Results to Gateways;
Step-11: End If
Step-12: End If

4. Proposed Work

This proposed work is validated with both the evaluative and network parameters [17, 18]. The accuracy (Ac), precision (Pr), sensitivity (sn), specificity (Sp), f-measure (Fm), and Mathew's correlation coefficients (MCC) are the evaluative parameters employed in this work, which are calculated based on equations 1-6. These equations are based on basically 4 words, i.e., T^a, T^b, F^a, and F^b are used for true and false positives and negatives, respectively, and constitute the confusion matrix [19, 24].

$$Ac = (T^a+T^b)/\,(T^a+T^b+F^a+F^b) \quad (1)$$

$$Pr = T^a/\,(T^a+F^a) \quad (2)$$

$$Sn = T^a/\,(T^a+F^b) \quad (3)$$

$$Sp = (T^b)/\,(T^b+F^a) \quad (4)$$

$$Fm = (2\times Pr\times Sn)/\,(Pr + Sn) \quad (5)$$

$$MCC = ((T^a+T^b)\text{-}(F^a+F^b))/\surd\,((T^a+F^a)(T^a+F^b)(T^b+F^a)(T^b+F^b)) \quad (6)$$

The classifiers, including the stacked classifier, were tested on CHDD, HHDD, and FHDD to determine which one performed best; the results are presented in Tables 3-5 and Figures 3-5, respectively. The stacked classifier is clearly the best option for the EML model in all of the tested datasets; hence this method should be seriously examined. It can be observed that achieving the highest accuracies of 82.65%, 80.21%, and 88.04% in the case of CHDD, HHDD, and FHDD, respectively, by applying a Stacked ensemble on the basic five ML classifiers. Consequently, the proposed model is trained with stacked EML on FHDD and implemented on various Master, Fog, and Cloud nodes.

Table 3. Results obtained on the CHDD dataset

Classifiers	Accuracy	Precision	Sensitivity	Specificity	F-Measure	MCC
RF	76.33	77.97	82.14	69.05	80.01	51.75
NB	75.51	78.33	81.03	67.51	79.66	48.96
KNN	78.57	81.67	83.05	82.35	71.79	55.09
ET	78.57	81.36	82.76	72.51	82.05	55.49
SVM	80.61	84.38	85.71	71.43	85.04	57.52
DT	76.53	80.01	81.36	69.23	80.67	50.82
Stacked	82.65	86.21	84.75	79.49	85.47	63.97

Table 4. Results obtained on the HHDD dataset

Classifiers	Accuracy	Precision	Sensitivity	Specificity	F-Measure	MCC
RF	76.04	78.95	80.36	70.01	79.65	50.55
NB	73.96	75.86	80.01	65.85	77.88	46.38
KNN	76.04	79.31	80.69	69.23	80.01	50.15
ET	76.04	78.95	80.36	70.01	79.65	50.55
SVM	78.13	82.26	83.61	68.57	82.93	52.51
DT	73.96	77.59	78.95	66.67	78.26	45.81
Stacked	80.21	83.93	82.46	76.92	83.19	59.15

Table 5. Results obtained on the FHDD dataset

Classifiers	Accuracy	Precision	Sensitivity	Specificity	F-Measure	MCC
RF	80.38	81.41	86.07	72.41	83.67	59.31
NB	77.51	79.69	82.93	69.77	81.27	53.23
KNN	80.38	81.54	86.18	72.09	83.79	59.14
ET	81.34	83.85	85.83	74.39	84.82	60.64
SVM	82.29	85.07	87.02	74.36	86.04	61.89
DT	78.47	81.39	83.33	71.08	82.35	54.78
Stacked	88.04	91.13	88.98	86.59	90.04	75.11

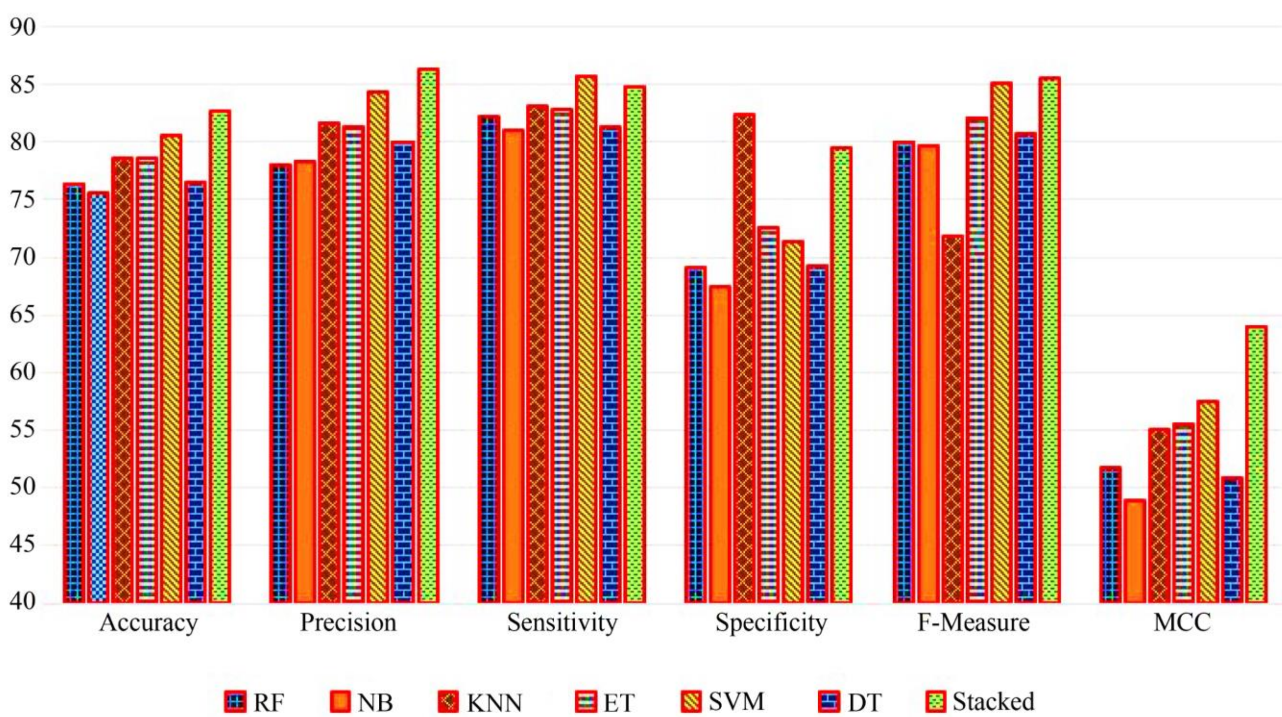

Fig. 3 Evaluative results obtained on the CHDD dataset

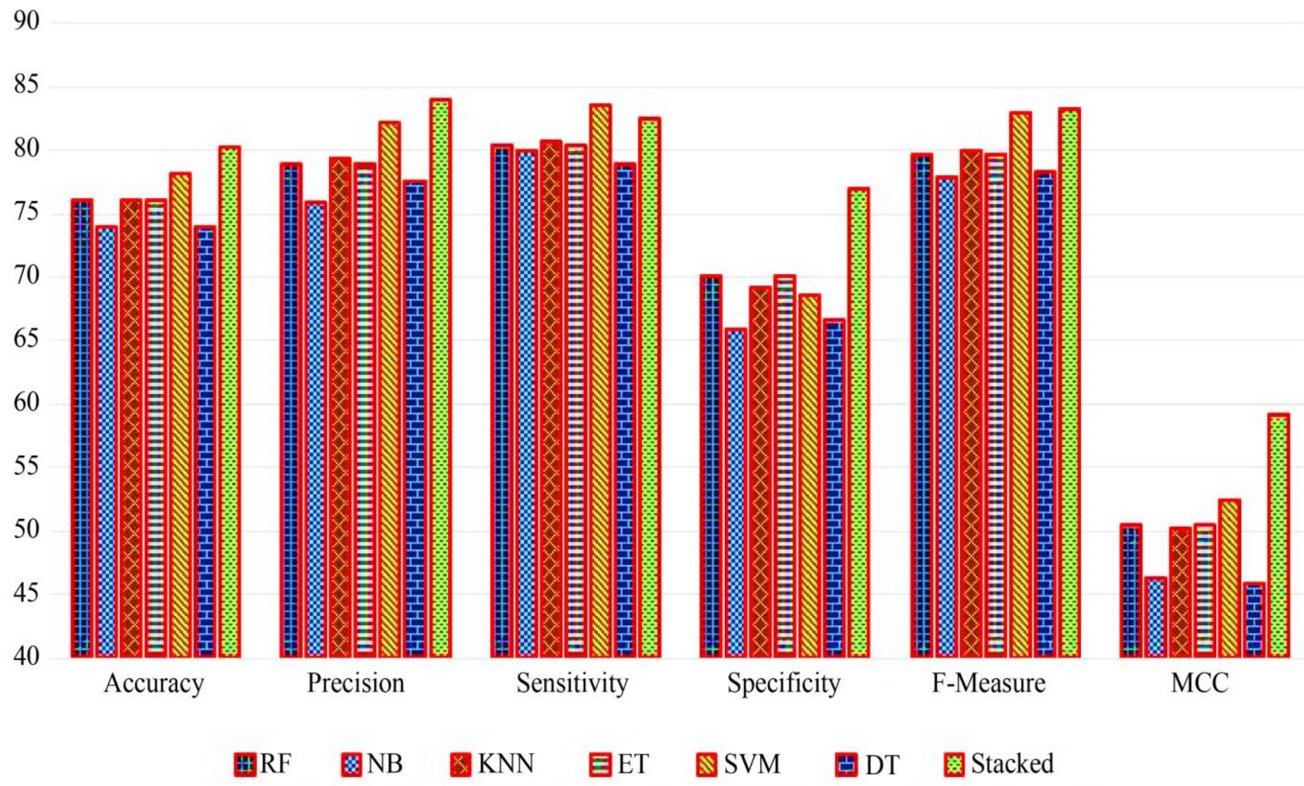

Fig. 4 Evaluative results obtained on the HHDD dataset

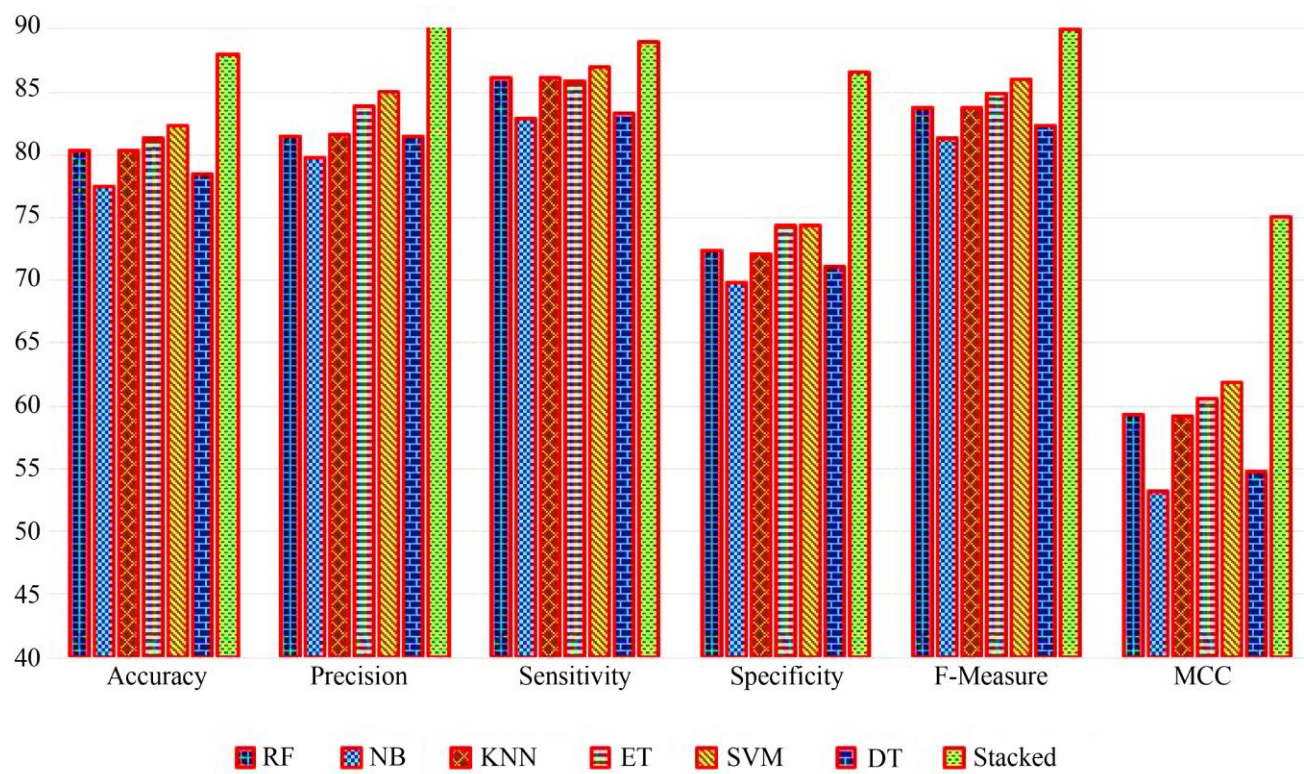

Fig. 5 Evaluative results obtained on the FHDD dataset

Various network parameters, including latency, processing time, bandwidth usage, and energy consumption, are also included, as shown in Table 6, to show that the Fog computing inclusion into the IoT-Cloud collaborations is effective in these terms. There are some configurations considered in this work as ”Order-1” for the Master node only, whereas ”Order-2 to Order-5” for the Master node with one, two, three, and four Fog worker nodes, respectively, and ”Order-6” for the Master node with Cloud center nodes. Four Raspberry Pi devices are used here as Fog worker nodes. Fig. 6 shows that Fog computing relatively consumes low latency compared to Cloud computing. The same can be shown in Figures 8 and 9 in terms of bandwidth usage and energy consumption. But, the inclusion of Cloud computing takes less time to process the job requested related to Fog computing, as shown in Fig. 7. It is clear from these that there are use cases where Fog computing excels over Cloud principles and others where it falls short. Consequently, the integrated approaches of Fog computing with IoT-Cloud computing collaboration enhance responses in real-time heart patients’ diagnosis.

Table 6. Results obtained based on various network parameters

Network Parameters	Order-1	Order-2	Order-3	Order-4	Order-5	Order-6
Latency (in ms)	17.9	23.4	27.6	29.1	34.8	1456.9
Processing Time (in ms)	1822.7	2456.4	2369.6	2845.1	3021.5	867.3
Bandwidth (in Kbps)	3.9	6.7	7.8	11.3	14.2	18.4
Energy Consumption (in Watt)	2.1	2.6	2.9	4.3	5.9	11.4

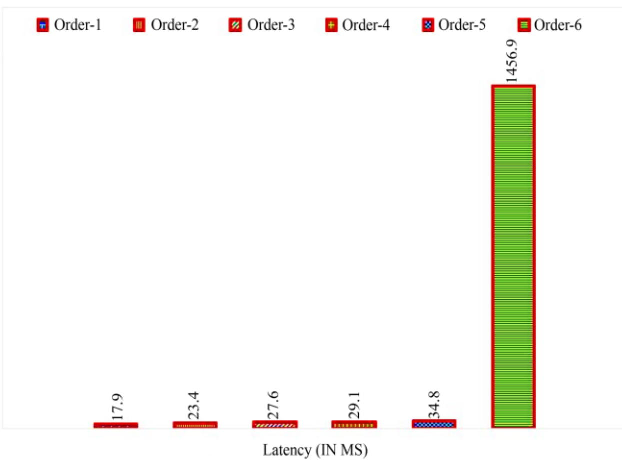

Fig. 6 Configurations-wise observed latencies (in ms)

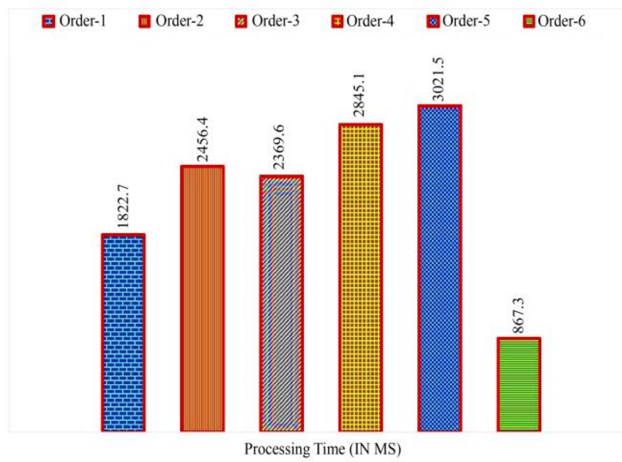

Fig. 7 Configurations-wise observed processing times (in ms)

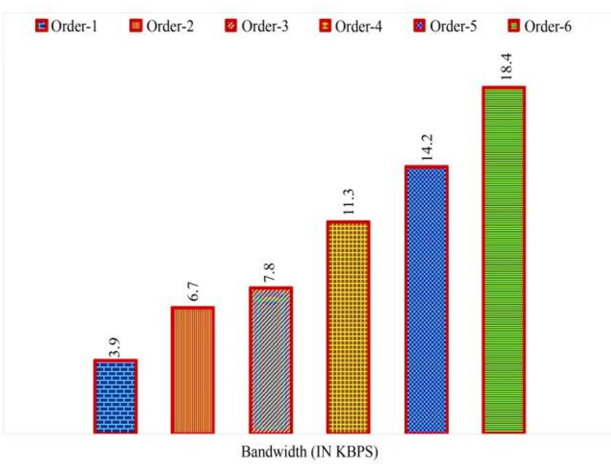

Fig. 8 Configurations-wise observed bandwidth (in kbps)

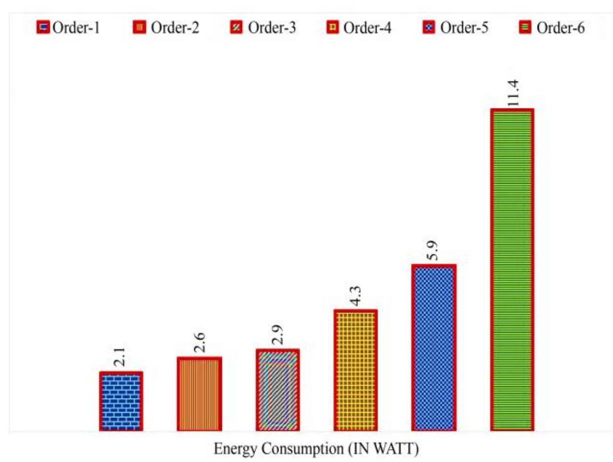

Fig. 9 Configurations-wise observed energy consumptions (in Watt)

Table 7. A Comparative Analysis of this Proposed work with some state-of-the-art works

Work	Employed Concepts					Employed Evaluative Parameters									
	EL	ML	FC	IoT	CC	Acc	Pre	Sen	Spe	FM	MCC	Lnt	PrT	Bnd	EnC
[5]			√	√	√							√			√
[6]	√		√	√	√	√						√	√	√	√
[7]		√	√	√	√								√		
[8]	√	√	√	√		√									
[9]			√	√	√	√	√	√	√	√	√				
[22]	√	√	√	√	√	√						√	√	√	√
[11]		√	√	√	√	√						√			
Proposed Work	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

It can be observed that this proposed approach on FHDD empowered with Fog computing concepts can be beneficial to society in terms of instantaneous and remote diagnosis of individuals related to heart diseases. Besides, to justify this proposed work, the comparison is employed, as shown in Table 7, considering the approaches used by various state-of-the-art works. Various abbreviations are included in this table, i.e., "LnT" for latency, "PrT" for processing time, "BnD" for Bandwidth usage, "EnC" for energy consumption, "√" for the involvement of the approaches and/or parameters, etc. The ensemble of ML approaches is included in this IoT, Fog, and Cloud computing integrated framework and justifies this proposed work in terms of various evaluative measures.

5. Conclusion and Future Scope

When Fog computing is employed with IoT installations, e-healthcare solutions are straightforward and uniform for patients. Because heart disease mortality is high, remote self-diagnosis will be successful. Formal IoT implications only employ Cloud computing techniques, which have several issues that can be fixed by integrating Fog, IoT, and Cloud concepts in this proposed work. The Cleveland and Hungarian datasets from the UCI-ML warehouse were used in this work. They were integrated into a single dataset, and five basic ML classifiers were used. The suggested method, especially on the fused dataset and when stacked as an ensemble classifier on these five ML algorithms, achieved the highest level of accuracy when compared to these five classifiers. The studies' relative better accuracy, precision, sensitivity, specificity, f-measure, and MCC values were 88.04%, 91.13%, 88.98%, 86.59%, 90.04%, and 75.11%, respectively. According to the experiments, this study's application of Fog computing principles allows it to instantaneously and remotely diagnose cardiac patients with the least amount of latency and energy utilization.

The expensive cost of this work, using a dataset with only 597 occurrences, which is unhelpful for deep learning trials, and using a single platform-based approach are some of its shortcomings. More research on various chronic illnesses utilizing more cutting-edge methods may solve the abovementioned limitations.

References

[1] C. Sowmiya, and P. Sumitra, "Analytical Study of Heart Disease Diagnosis Using Classification Techniques," *IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing*, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[2] Abhilash Pati, Manoranjan Parhi, and Binod Kumar Pattanayak, "IHDPM: An Integrated Heart Disease Prediction Model for Heart Disease Prediction," *International Journal of Medical Engineering and Informatics*, vol. 14, no. 6, pp. 564-577, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Abhilash Pati et al., "Diagnose Diabetic Mellitus Illness Based on IoT Smart Architecture," *Wireless Communications and Mobile Computing*, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Srinivasa Rao Patri, and L. Nithyanandan, "Network throughput Optimization for Relay Based NB-CR-IoT Wireless Body Area Network," *International Journal of Engineering Trends and Technology*, vol. 70, no. 9, pp. 148-154, 2022. [CrossRef] [Publisher Link]

[5] Anand Paul et al., "Fog Computing-Based IoT for Health Monitoring System," *Journal of Sensors*, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] Shreshth Tuli et al., "Healthfog: An Ensemble Deep Learning Based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in Integrated IoT and Fog Computing Environments," *Future Generation Computer Systems*, vol. 104, pp. 187–200, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] P. G. Shynu et al., "Blockchain-Based Secure Healthcare Application for Diabetic-Cardio Disease Prediction in Fog Computing," *IEEE Access,* vol. 9, pp. 45706-45720, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Subarna Shakya, and P. P. Joby, "Heart Disease Prediction using Fog Computing based Wireless Body Sensor Networks (WSNs)," *IRO Journal on Sustainable Wireless Systems*, vol. 3, no. 1, pp. 49–58, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] K. Butchi Raju et al., "Smart Heart Disease Prediction System with IoT and Fog Computing Sectors Enabled by Cascaded Deep Learning Model," *Computational Intelligence and Neuroscience,* 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] S. Aiswarya et al., "Latency Reduction in Medical IoT Using Fuzzy Systems by Enabling Optimized Fog Computing," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 12, pp. 156-166, 2022. [CrossRef] [Publisher Link]

[11] Ali Golkar et al., "A Priority Queue-Based Telemonitoring System for Automatic Diagnosis of Heart Diseases in Integrated Fog Computing Environments," *Health Informatics Journal*, vol. 28, no. 4, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] Heart Disease, 1988. [Online]. Available: http://archive.ics.uci.edu/ml/datasets/heart+Disease

[13] Shreshth Tuli et al., "FogBus: A Blockchain-based Lightweight Framework for Edge and Fog Computing," *Journal of Systems and Software*, vol. 154, pp. 22–36, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[14] R. Surendiran, and K. Raja, "A Fog Computing Approach for Securing IoT Devices Data using DNA-ECC Cryptography," *DS Journal of Digital Science and Technology,* vol. 1, no. 1, pp. 10-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Emad K. Qalaja et al., "Inclusive Study of Fake News Detection for COVID-19 with New Dataset using Supervised Learning Algorithms," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 8, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Mohammad Alnabhan et al., "Hyper-Tuned CNN Using EVO Technique for Efficient Biomedical Image Classification," *Mobile Information Systems,* 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Abhilash Pati, Manoranjan Parhi, and Binod Kumar Pattanayak, "A Review on Prediction of Diabetes Using Machine Learning and Data Mining Classification Techniques," *International Journal of Biomedical Engineering and Technology*, vol. 41, no. 1, pp. 83-109, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Bibhuprasad Sahu et al., "Hybrid Multiple Filter Embedded Political Optimizer for Feature Selection," *International Conference on Intelligent Controller and Computing for Smart Power*, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Abhilash Pati et al., "Predicting Pediatric Appendicitis using Ensemble Learning Techniques," *Procedia Computer Science,* vol. 218, pp. 1166–1175, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] G. Vinobala, and M. Piramu, "Monitoring of Industrial Electrical Equipment Using IoT," *SSRG International Journal of Computer Science and Engineering*, vol. 8, no. 1, pp. 13-18, 2021. [CrossRef] [Publisher Link]

[21] Abhilash Pati, Manoranjan Parhi, and Binod Kumar Pattanayak, "HeartFog: Fog Computing Enabled Ensemble Deep Learning Framework for Automatic Heart Disease Diagnosis," *Smart Innovation, Systems and Technologies,* vol. 286, pp. 39–53, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Parag Verma et al., "FETCH: A Deep Learning-Based Fog Computing and IoT Integrated Environment for Healthcare Monitoring and Diagnosis," *IEEE Access*, vol. 10, pp. 12548-12563, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] Abhilash Pati et al., "An IoT-Fog-Cloud Integrated Framework for Real-Time Remote Cardiovascular Disease Diagnosis," *Informatics*, vol. 10, no. 1, p. 21, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Saroja Kumar Rout et al., "Early Detection of Sepsis Using LSTM Neural Network with Electronic Health Record," *Smart Innovation, Systems and Technologies*, vol. 317, pp. 201-207, 2022. [CrossRef] [Google Scholar] [Publisher Link]