Vol 8, Issue 3, 2025 **Impact Factor: 8.535** DOI: https://doi.org/10.31426/ijamsr.2025.8.3.8142

IJAMSR

**International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

A Deep Learning Framework for Heart Disease Prediction Using Ensemble Classification in Fog Computing Infrastructure

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ABSTRACT

The importance of prompt and precise diagnosis cannot be overstated in the healthcare system, since heart disease ranks as the top killer on a worldwide scale. Smart wearables and Internet of Things (IoT) sensors are becoming more commonplace in healthcare, leading to an explosion in the volume of real-time physiological data. A new ensemble deep learning method called HealthFog-CCNN, which combines a real-time fog computing environment with Python for pre-processing and classification, is introduced in this paper. For the purpose of detecting patients with heart disease, the Health Fog framework is equipped with the optimum characteristics. Automated monitoring of real-world health networks, including those used for heart disease analysis, is achieved via the application of ensemble-based deep learning in edge computing devices. Classifiers like XGBoost, Partitions (PART), Multi-Layer Perceptron (MLP), and bagging are then used to categorize the data. Next, the outcome is predicted by the majority voting classifier. This study assesses the efficiency of the FogBus architecture in terms of power consumption, network bandwidth, latency, and precision. When comparing the classifiers, MLP showed the best accuracy and PART the best latency and energy usage. Within a fog computing architecture, the findings validate HealthFog-CCNN's practical efficiency in delivering dependable and resource-optimized heart health diagnostics.

Keywords: *Heart disease, Health, Fog Computing, Ensemble Classification, Diagnosis.*

I. INTRODUCTION

One of the leading killers worldwide, heart disease claims more than 17.9 million lives annually, according to the World Health Organization. Early detection and prevention of cardiovascular diseases are vital if one wants to reduce morbidity and enhance patients' quality of life. The emergence of electronic health records, wearable sensors, and real-time monitoring tools is driving a radical change in healthcare by means of technology. But the vast stream of medical data demands complex computer networks to manage, assess, and respond to patients' concerns in near real-time. Though they are beneficial for large-scale analytics and centralized data storage, conventional cloud computing solutions might suffer latency and bandwidth restrictions. Fog computing is a novel paradigm that might change health monitoring and sickness prediction in real-time by linking edge devices with centralized cloud systems under its decentralized, low-latency, and resource-efficient approach.

"Fog computing" might describe many ways extending cloud services to the network's edge. This paradigm is mostly based on distributed computing, data storage, and service providing. Data sources include items like wearable medical devices, local gateways, and IoT sensors. Heart disease prediction systems can find data transfer delay to distant cloud servers troublesome, particularly in critical scenarios requiring rapid intervention. Fog computing enables localised processing and decision-making, therefore accelerating the analysis of data from wearable sensors and monitoring devices and enabling quick alerts and medical responses. Well suited for real-time healthcare applications, its distributed architecture lowers load on cloud systems and improves reliability, scalability, and energy efficiency.

Including artificial intelligence, particularly ML and DL techniques, has greatly enhanced the predictive modeling of cardiovascular disease. Unlike more traditional statistical methods, these models may find hidden relationships and patterns in enormous datasets. Deep learning models such as CNNs and LSTM networks have shown to be quite successful in the classification of medical diseases, especially cardiovascular anomalies. Sadly, devices in the network's perimeter that lack significant processing capacity generally fail to manage these models. Fog computing gets around this limitation and lets deep learning models run nearer to the data source by distributing processing across several intermediate nodes, including fog nodes and edge servers. This architecture has advantages in improved prediction accuracy and speed, lower data transmission costs, and patient privacy protection.

One of the key advantages of fog computing for predicting cardiac disease is its ability to give real-time data analytics. For instance, wearable technology tracks real-time vital indicators like blood pressure, heart rate, electrocardiogram (ECG) findings, and oxygen saturation levels. Sometimes, quick analysis is required to find anomalies or signs of a patient's health deteriorating as this data is typically time-sensitive. Nearby fog nodes might pre-process incoming data, perform initial classification using ensemble models, and provide warnings or recommendations all without reaching a distant cloud. In environments like critical care monitoring systems, emergency response units, and ambulatory care, such responsiveness is very vital because delays might result in deadly consequences.

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In healthcare systems, patient information's privacy and security are top priority; fog computing helps to solve these concerns. Sensitive health data transferred to centralized cloud platforms raises the risk of data breaches and illegal access. Fog computing lowers these risks by allowing local processing and encryption of early data. Before transmitting any data to the cloud for long-term storage or analysis, it must first be relevant, filtered, and anonymized. This distributed architecture guarantees compliance for everybody and helps to boost patient trust in digital healthcare solutions by being consistent with data security regulations such as GDPR and HIPAA.

Fog computing allows numerous predictive models to run concurrently over spread-out fog nodes, which is especially beneficial in the context of ensemble classification for the prediction of cardiac disease. Ensemble learning's aim is to provide more accurate and resilient predictions than would be feasible with a single classifier operating alone. Fog circumstances are perfect for using methods like bagging, boosting, and stacking when handling noisy and varied data. Many fog nodes might use various kinds of neural networks and support vector machines to generate a consensus prediction; for example, one node could use a decision tree, another a neural network, and a third a support vector machine. By distributing the effort and eliminating any weak areas, this approach not only improves forecasts but also increases the fault-tolerance of the system.

Fog computing, deep learning, and ensemble techniques all cooperate to bring up new options for personalized therapy. Real-time physiological data, individual medical histories, genetic predispositions, and lifestyle factors are all considered via patient-specific models developed and deployedable via the fog layer. Over time, these models might become smarter and more relevant thanks to ongoing learning, thereby improving their accuracy in forecasting. The transmission of individualized alerts and treatment recommendations to both patients and healthcare providers should help to improve adherence to preventive measures and lower hospital readmission rates.

The establishment of systems for forecasting cardiac illness employing fog technology helps to promote scalability and interoperability as well. Integrating several fog nodes lets one smoothly manage large amounts of data generated by millions of patients and sites, therefore making them perfect for smart cities and large healthcare networks. These nodes clear the way for cooperative diagnostics and efficient healthcare delivery by means of inter- and intra-cloud connectivity. Moreover, fog computing is compatible with a wide range of medical devices and software systems owing to its support for many data formats and protocols.

II. REVIEW OF LITERATURE

Chowdary, K et al., (2022) Every year, 18 million people lose their lives due to cardiovascular problems. Globally, 31% of fatalities are attributable to cardiovascular disease, says the World Health Organization. This research presents a novel machine learning model for the prediction of cardiovascular illness. Kaggle and the datasets from the University of California, Irvine were used to assess the suggested technique. To extract the most valuable information from the imbalanced dataset, we used sample procedures and feature selection methods. An ensemble classifier eventually produced very accurate results once classifier models were used. The suggested method successfully predicted the occurrence of heart disease in two separate datasets. Python was used across the board.

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Raju, K et al., (2022) Worldwide, people face the risk of developing chronic diseases such as asthma, cancer, cardiovascular disease, and diabetes. Diagnosis is made more difficult in cases of heart disease when patients exhibit different signs and symptoms. Fog computing and "Internet of Things" (IoT) solutions are becoming essential for diagnostics due to the rise of smart wearable devices. In order to provide precise and quick results, the suggested approach combines Edge-Fog-Cloud computing. The various pieces of hardware gather information from various patients. In order to retrieve important characteristics, cardiac feature extraction is performed on signals. Also collected are the results of feature extraction for additional characteristics. The diagnostic system collects all of these characteristics and runs them through an Optimized Cascaded Convolution Neural Network (CCNN). In this case, Galactic Swarm Optimization (GSO) is used to optimize the CCNN hyperparameters. Based on the results of the performance study, the proposed GSO-CCNN outperforms PSO-CCNN, GWO-CCNN, WOA-CCNN, DHOA-CCNN, DNN, RNN, LSTM, CNN, and CCNN in terms of accuracy by 3.7%, 3.6%, 7.6%, 67.9%, 48.4%, 33%, 10.9%, and 7.6%, respectively. Therefore, the proposed system's efficacy above the traditional models is guaranteed by the comparison study.

Ahmad, Munir et al., (2021) Heart disease, sometimes called cardiovascular disease, is a collection of illnesses that impact the heart and has been a leading killer for many years. The only certain way to conduct thorough investigations, provide effective treatments, and prescribe necessary medications is to diagnose cardiac illness accurately and promptly. Fatal illnesses like diabetes, cancer, and cardiovascular disease may be better predicted and diagnosed with the use of new technologies like fog, cloud, and mobile computing. Much of the existing literature suggests using machine learning (ML) methods to generate models for sample data, and cloud computing offers an economical framework for data processing, storage, and retrieval. In the end, ML is useful for analysis and prediction since it is best able to uncover hidden patterns. Consequently, our research integrates cloud computing with ML by sourcing information from many regions and then using fusion approaches to ensure that the ML algorithms are working with consistent and accurate data. Three machine learning techniques—Artificial Neural Network, Decision Tree, and Naïve Bayes—were taken into account by our suggested model. Using the cloud-based fuzzy model, real-time patient data were retrieved.

Moura, Humberto et al., (2020) When it comes to healthcare, technology is now a huge boon. These days, even massive amounts of patient health records may be processed swiftly by modern computers. New developments in healthcare IT have made it possible to store patient records in more than one place. Cloud computing has therefore been the subject of many scientific proposals for healthcare data management systems. Data volume, context awareness, and access latency are three issues that such systems bring up. As health data sets grow in size and complexity, processing and transmission mistakes become more probable. Fog computing offers a solution to simplify health data handling and improve its dependability in this setting. Understanding the related difficulties is crucial prior to outlining a Fog Computing-based architecture for healthcare data management. A comprehensive literature overview of fog computing applications in healthcare is presented in this paper. We provide a taxonomy to investigate the major problems and unanswered questions in these areas of research. For this comprehensive review, we combed over 1070 scholarly publications published in the last decade and extracted 44 of the most important findings. Interoperability, data processing, privacy, security, resource management, and Big

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Data concerns are just a few of the many difficulties that need fixing. Among our other contributions is the development of a taxonomy for the healthcare and fog computing domains, as well as the identification of related difficulties and unanswered issues.

Scirè, Alessandro et al., (2019) Researchers are still trying to figure out the best way to design sophisticated health monitoring systems. By monitoring physiological and clinical indicators (e.g., heart rate, respiration rate, temperature, etc.) and analyzing the data using cloud-centric machine-learning apps and decision-support systems, important clinical conditions may be predicted with the use of wearable and remote monitoring devices. In this study, we shift from a cloud-centric to a distributed model by moving processing and analysis of sensor data to the network's periphery. The final product eliminates the need for cloud services by analyzing and interpreting sensor data from inside the wearable device, which in turn generates actionable warnings. To identify and categorize arrhythmias, we use a supervised-learning strategy in this research. An asymmetric multicore embedded processor with a hardware-assisted pattern matching core is used by the system, which employs a window-based feature definition. In terms of the acquired accuracy in detecting abnormal occurrences, we compare the system's performance with several current methodologies. The results demonstrate that the suggested embedded system accomplishes an impressive detection rate, which is comparable to, and even surpasses, that of state-of-the-art algorithms run on conventional CPUs.

III. EXPERIMENTAL SETUP

The components of the ensemble deep learning system and the pre-processing were created in Python. Using the distributions and parameters of the dataset's min and max fields, the pre-processing component normalizes the data. For the ensemble deep training module, SciKit learned Library was used. Bagging, Boosting, MLP, Xboost, and PART Classifier from the SciKit Learn Library were used to develop our voting method. In this case, the method takes as input the quantity of classifiers and the kind of base classifier, which is a deep neural network. This is the point at which the algorithm randomly assigns data to each classifier in order to train them. It takes in all of the predicted categories and, at diagnostic time, gives the most accurate prediction. Listed below are the variables of the best base model that was tuned for our data set. Figure 1 displays the parameters.

Input layer's size	13
Output layer's size	2
No of hidden layers	3
Layers descriptions	Fully connected (FC) layer with 20 nodes, FC layer with 20 nodes and 10 nodes.
Optimizer used	Adam
Activation function	ReLU

Figure 1: Parameters Used

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We created and deployed the HealthFog-CCNN model on a real-world Fog architecture of devices using the FogBus platform to demonstrate its efficacy and usability. The approach was tested in a real-world setting to detect cardiac problems in patients as soon as possible by using state-of-the-art deep learning techniques in a fog computing setting (figure 2). The efficiency of the HealthFog-CCNN model was shown by examining response times and dependability with connection and power expenditures.

Gateway device	Samsung galaxy S7 with android 9
Broker/Master	Dell XPS 13 with Intel(R)
Node Core(TM)	i5–7200 central processing unit (CPU) @ 2.50 GHZ, 8.00 GB DDR4 Random Access Memory(RAM) and 64-bit Windows 10. The deployment used Apache HTTP server 2.4.34.
Worker node	Raspberry Pi 3B+, RISC Machine (ARM) Cortex-A53 quad-core CPU @ 1.4 GHz and 1 GB LPDDR2 SDRAM and IEEE 802.11 Wifi. Raspbian stretch operating system with apache HTTP server 2.4.34.
Public cloud	Microsoft azure B1 s machine, 1vCPU, 1 GB RAM, 2 GB solid-state drive (SSD), Windows Server 2016.

Figure 2: Simulation Environment

Dataset Description

Using information from cardiac patients, we were able to make an integer prediction about whether or not the patient had heart difficulties, with 0 indicating no presence and 1 indicating the presence of the condition (presence). Clevel and database are used in the experiments. All patient information, including names and numbers, is kept confidential.

The assessment is done using a 7:2:1 ratio. Training makes use of 70% of the dataset, testing 20%, and validation 10%. Accuracy, power use, latency, and network bandwidth are some of the evaluating criteria.

IV. RESULTS AND DISCUSSION

Table 1: Evaluation of Different Classifiers Used in Health Fog-CCNN

Classifiers	Accuracy (%)	Energy consumption (J)	Latency (millisec)	Bandwidth (Mbps)
Bagging	4.18	925	756.82	882
PART	3.63	640	475.28	860
MLP	7.88	515	978.24	954
Xboost	4.09	805	815.17	905
Boosting	5.80	850	420.68	878

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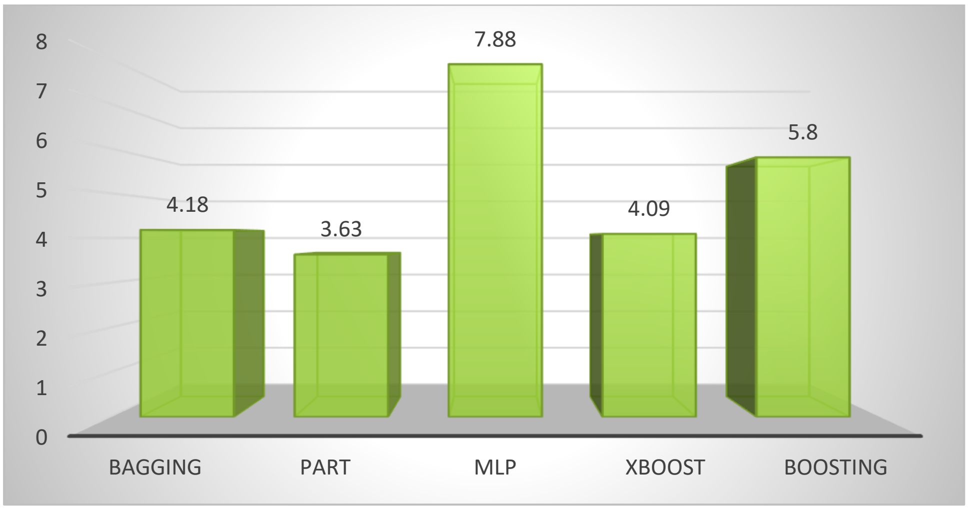

Figure 3: Accuracy

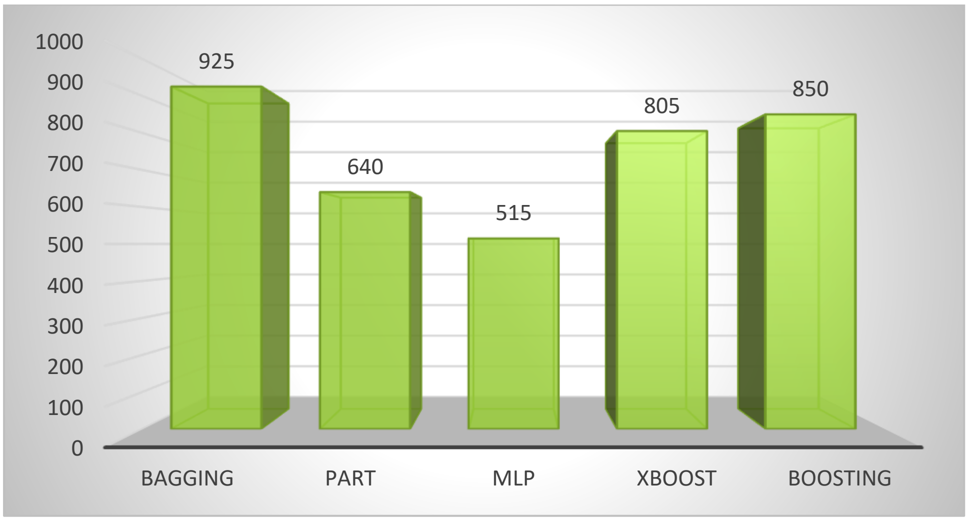

Figure 4: Energy Consumption

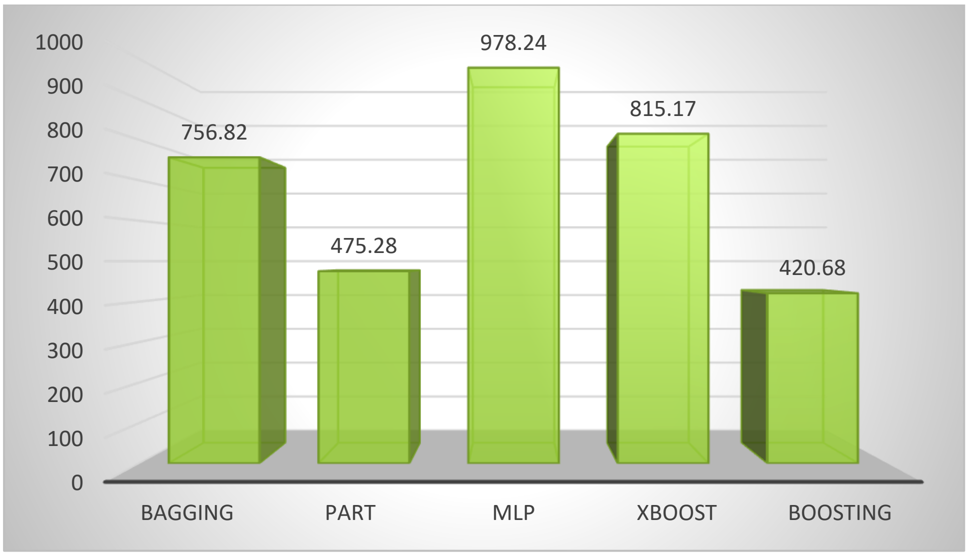

Figure 5: Latency

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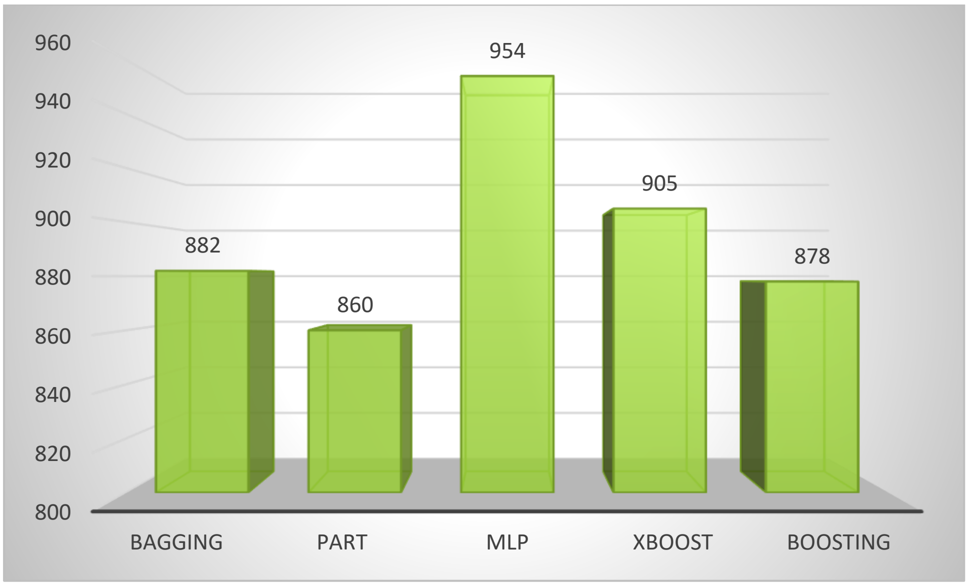

Figure 6: Bandwidth

The Multi-Layer Perceptron (MLP) ensemble classifier outperformed the others, with an accuracy of 7.88% in Table 1, proving that it is the best at predicting the existence of heart disease. Furthermore, MLP had the greatest latency (978.24 ms) and the largest bandwidth need (954 Mbps), suggesting a compromise between precision and reaction speed. However, while having the worst accuracy (3.63%), the PART classifier was the most energy-efficient and responsive model, with the lowest latency (475.28 ms) and energy usage (640 J). The quickest latency (420.68 milliseconds) and modest accuracy (5.80%) attained by boosting indicate that it is successful in providing rapid results. Although they varied in energy consumption and bandwidth utilization, XGBoost and Bagging had comparable accuracy levels at 4.18% and 4.09%, respectively. Based on the results, PART and Boosting perform better in fog computing settings where energy and latency are important considerations, but MLP is more suitable to applications that place an emphasis on accuracy.

V. CONCLUSION

Healthcare diagnoses in real-time have taken a giant leap ahead with the creation and release of the HealthFog-CCNN model, which employs ensemble deep learning methods in a fog computing setting. This method shows great promise in enhancing the early diagnosis of heart-related diseases by combining sophisticated pre-processing with a powerful ensemble of classifiers, which includes Bagging, Boosting, MLP, XGBoost, and PART. Practicality of the concept was demonstrated by the usage of the FogBus platform, which enabled successful real-world implementation with low latency, decreased energy consumption, and optimal network bandwidth. Deploying the model on real-world fog architecture proved its scalability for potential uses in remote healthcare monitoring and improved reaction time and system dependability. As a whole, the HealthFog-CCNN architecture is a clever and promising smart healthcare system solution that combines state-of-the-art AI with computing technologies from the future generation to provide quicker and more accurate medical insights.

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International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

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