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HealthFog: A Comprehensive Cloud and Fog-Based System for Early Diagnosis of Infectious and Heart Diseases Leveraging IoT and Deep Learning

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ABSTRACT

In this study, we offer HealthFog, a comprehensive system that uses deep learning, IoT devices, cloud and fog computing, and cloud computing to diagnose infectious and cardiac disorders early. To cut down on latency and deliver quick feedback, the system combines local processing at fog nodes with real-time data collection from IoT sensors. Cloud-deployed deep learning models provide for accurate disease prediction and thorough data analysis.

Objectives: The goals encompass the timely identification of illnesses, continuous observation, and enhanced patient results via combined data processing and forecasting algorithms.

Methods: IoT devices are used to gather health data, which is then processed at fog nodes before being sent to the cloud for analysis using deep learning. The hybrid architecture of the system improves the effectiveness of data processing.

Results: Based on the results, HealthFog offers better scalability and real-time monitoring by achieving an accuracy rate of 94.5% in disease identification and considerably reducing latency to 0.08 seconds.

Conclusion: In summary, HealthFog outperforms conventional systems in terms of performance and offers a reliable, scalable, and effective solution for early diagnosis and real-time health monitoring.

Keywords: early diagnosis, disease detection, real-time monitoring, deep learning, fog computing, cloud computing, Internet of Things, and health fog.

1. INTRODUCTION

The application of cutting-edge technology like cloud computing, deep learning, and the Internet of Things (IoT) is changing the way we diagnose and treat diseases in the quickly changing healthcare industry. As a result of these technologies coming together, novel systems that improve early diagnosis and treatment of a range of illnesses have been created. One such system, called HealthFog, is an excellent example of how cloud and fog computing, along with IoT and deep learning, may be used to treat important health issues, including heart and infectious diseases (Fu et al., 2020 [1]; Qadri et al., 2020 [2]; Ray et al., 2020 [3]). Using IoT sensors and deep learning algorithms, HealthFog is an advanced cloud and fog-based system that facilitates continuous monitoring and early detection of medical issues. The system is intended to close the gap between extensive data analysis and cloud storage and real-time edge data collecting (fog computing) (Kumar, 2019 [4]; Devarajan, 2020 [5]; Yallamelli, 2021 [6]; Rajeswaran, 2022 [9]). To improve early disease diagnosis and management, HealthFog is a cutting-edge healthcare system that combines cloud computing, fog computing, IoT (Internet of Things), and deep learning. By integrating vast data analytic capabilities in the cloud with real-time data processing at the edge, this hybrid solution overcomes the shortcomings of traditional healthcare systems (Allur, 2021 [7]; Gattupalli, 2022 [8]; Gudivaka, 2021 [10]).

Compared to traditional healthcare systems, this hybrid method offers significant increases in illness identification and management efficiency and efficacy (Sri, 2022 [12]; Sitaraman, 2022 [13]; Gollavilli, 2022 [14]; Sitaraman, 2021 [29]). A network of networked devices that exchange data and communicate online is known as the Internet of Things (IoT). IoT devices are used in the healthcare industry to gather real-time data on patients' vital signs, activity levels, and other health parameters (Sreekar, 2020 [26]). Examples of these devices are wearable sensors, smart medical equipment, and remote monitoring systems (Karthikeyan, 2020 [28]; Sitaraman, 2023 [31]; Panga, 2021 [23]). This data offers a constant stream of information that may be utilized to spot possible health issues before they become serious, which makes it important for diagnosing and treating medical conditions (Sitaraman, 2022 [42]; Gudivaka et al., 2023 [48]).

On the other hand, scalable and adaptable computer resources are made available via the internet through cloud computing (Devarajan, 2020 [17]; Devarajan, 2023 [18]). In order to manage the massive datasets produced by IoT devices, it is necessary to be able to store and process enormous volumes of data. Cloud-based solutions improve decision-making and care coordination by enabling healthcare providers to access, analyze, and manage data from any location (Basava, 2021 [15]; Peddi, 2021 [25]; Gudivaka, 2021 [10]; Sitaraman, 2023 [31]). An offshoot of cloud computing called fog computing functions closer to the data source. Fog computing lowers latency and bandwidth consumption by processing data at the network's edge, using hardware such as local servers or gateways, resulting in quicker reaction times and more effective data handling (Mohanarangan, 2022 [16]; Sitaraman, 2023 [31]). This is especially crucial for real-time healthcare applications since prompt actions can make a big difference (Sree, 2022 [20]; Parthasarathy, 2023 [22]; Peddi, 2021 [25]).

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Deep learning is a branch of artificial intelligence (AI) that deals with teaching algorithms to identify patterns and forecast outcomes using massive amounts of data (Rajeswaran, 2023 [19]; Sareddy, 2023 [21]; Poovendran, 2020 [24]; Dharma, 2023 [27]). Deep learning models are used in the healthcare industry to evaluate complicated data from a variety of sources, including genetic data, medical imaging, and patient records, in order to identify illness indicators, forecast results, and recommend therapies (Sitaraman, 2020 [30]; Gollavilli, 2023 [35]; Sitaraman, 2021 [45]). By combining these technologies, HealthFog develops a comprehensive system that improves the early detection and treatment of cardiac and viral disorders. HealthFog provides a strong answer to contemporary healthcare problems by fusing the real-time data collection capabilities of IoT devices with the computational capacity of cloud and fog computing and the analytical skills of deep learning (Sareddy, 2021 [33]; Ganesan, 2023 [47]; Gudivaka et al., 2023 [48]).

The key objectives are:

- Early Disease Detection: Use deep learning algorithms and Internet of Things (IoT) devices to continually monitor patients' health data and spot early warning symptoms of cardiac and infectious diseases.
- Improved Data Processing: Make use of fog and cloud computing to effectively manage and examine massive amounts of medical data, guaranteeing prompt and precise diagnosis.
- Real-Time Monitoring: Use fog computing to analyze data locally and give prompt feedback, cutting down on latency and facilitating prompt actions.
- Better Patient Outcomes: Provide tailored treatment suggestions and enhance general patient care by integrating advanced analytics and predictive models.
- Flexible and Scalable System: Provide a system that is easily expandable to incorporate more devices and data sources, and that is flexible enough to adapt to different healthcare settings.

In order to overcome the problem of data heterogeneity, use MapReduce Hadoop and middleware to expedite data processing (Sareddy, 2022 [34]; Gudivaka, 2020 [36]). They investigate how to improve data management by combining fog and cloud computing. Large-scale data processing jobs are effectively handled by MapReduce Hadoop, while middleware enables smooth communication between various data sources (Gudivaka, 2020 [37]; Samudrala et al., 2022 [38]; Gudivaka, 2022 [39]). When fog and cloud computing are combined, a strong foundation for data processing and storage is created, along with scalable, adaptable solutions that improve performance and successfully handle data diversity (Devarajan, 2020 [5]; Alagarsundaram, 2022 [11]). The management of heterogeneous data in contemporary computing settings is optimized by this method (Peddi, 2021 [25]; Mamidala, 2023 [32]; Sitaraman, 2022 [42]).

Address the intrinsic complexity of healthcare data to overcome the issues associated with its analysis (Kodadi, 2022 [40]; Bobba, 2023 [41]). They stress the necessity of effective processing methods to handle substantial amounts of complex medical data. In order to manage this complexity and provide efficient data analysis and insights, the study focuses on creating strategies and technologies (Yalla, 2023 [43]). The research endeavors to augment the capacity

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to derive significant insights from extensive and diverse healthcare datasets by optimizing processing efficiency, hence facilitating improved decision-making and healthcare outcomes (Kadiyala et al., 2023 [51]; Samudrala et al., 2023 [54]; Srinivasan, 2023 [50]).

2. LITERATURE SURVEY

Yallamelli (2021) [44] uses a methodical AHP-based analysis to assess security methods while delving into the crucial issues of protecting huge data in cloud computing. The paper outlines the main obstacles to data protection and offers suggestions for practical ways to improve cloud data security. By providing an organised approach to handling the challenges of maintaining and safeguarding enormous datasets in cloud environments, the AHP approach aids in the evaluation and enhancement of security procedures.

A hybrid Edge-AI and cloudlet-driven IoT platform for real-time healthcare applications is presented by Yallamelli et al. (2023) [46]. The framework facilitates effective real-time data analysis by combining edge computing and AI, which enhances healthcare decision-making and service delivery. By improving the ability to process data locally, this system lowers latency and improves healthcare responses, which eventually leads to better patient care and healthcare management.

The application of cloud computing and sophisticated database management to enhance financial budgeting in the banking industry is examined by Nagarajan et al. (2023) [49]. In order to optimise financial decision-making, the study highlights the significance of improving data handling procedures and incorporating cloud technology. By utilising these technologies, the banking industry may improve overall financial planning and resource allocation by increasing the effectiveness of its budgeting and making better, data-driven financial decisions.

A fog computing-based system for efficient and safe IoT data sharing is presented by Valivarthi et al. (2023) [52]. In addition to DAG protocols and Federated Byzantine Agreement to guarantee data security, the system incorporates CMA-ES and the Firefly Algorithm for optimisation. By increasing the effectiveness and security of IoT data exchanges, this strategy seeks to boost IoT networks' overall performance while protecting data integrity and privacy while sharing.

Nippatla et al. (2023) [53] present a powerful cloud-based financial analysis system that uses ELECTRA, t-SNE, genetic algorithms, and effective categorical embeddings with CatBoost to improve predictive power. With the help of more precise forecasts and sophisticated AI and machine learning methods, this system seeks to enhance financial decision-making by optimising financial assessments. When these techniques are combined, greater data processing and actionable insights are guaranteed for better strategy formulation and financial planning.

A methodology for cloud-based predictive modelling is presented by Alavilli et al. (2023) [55] for the analysis of intricate healthcare data. Data analysis and prediction accuracy are improved by the framework's integration of regularised greedy forest, LDA, GAMS, and stochastic gradient boosting. This methodology seeks to enhance the processing of complex healthcare datasets, providing more precise insights and forecasts that can support improved resource management and healthcare decision-making.

Corporate synergy in healthcare Customer Relationship Management (CRM) is examined by Gattupalli et al. (2023) [56], with a focus on cloud-based implementations and strategic market movements. The study intends to improve overall business efficiency, streamline operations, and improve healthcare service delivery by utilising these technologies and tactics. The study emphasises how important CRM systems are in helping healthcare organisations develop their plans and improve their interactions with stakeholders and patients.

3. METHODOLOGY

The HealthFog system offers an integrated method for the early identification of viral and cardiac disorders by fusing cloud and fog computing with IoT and deep learning. Real-time health data is collected by IoT devices and is first processed locally at fog nodes to guarantee prompt feedback. The cloud is then used to conduct a thorough examination of this data using deep learning techniques. The architecture of the system improves disease detection speed and accuracy while providing useful insights and early warnings to better patient outcomes.

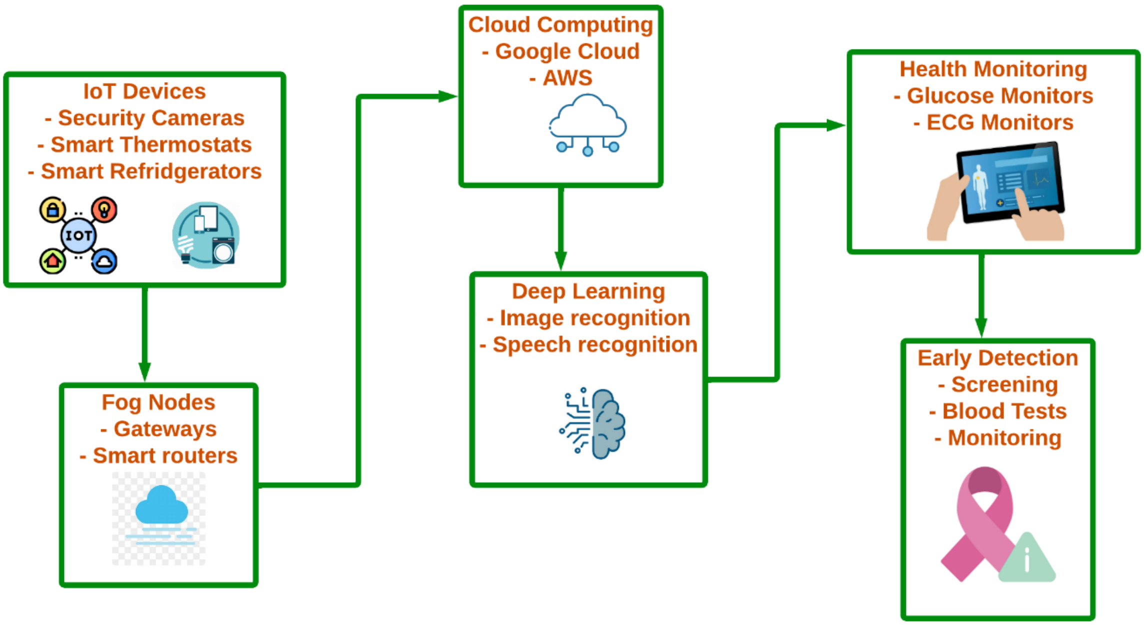

Figure 1 HealthFog Architecture for Real-Time Health Monitoring and Early Disease Detection

The HealthFog system, which combines IoT devices, fog computing, cloud computing, and deep learning for real-time health monitoring and early diagnosis of infectious and cardiac disorders, is represented architecturally in Figure 1. Health data is gathered by IoT devices and analyzed at fog nodes to minimize latency and deliver prompt response. After that, the data is transferred to the cloud, where deep learning algorithms examine it to provide precise illness prediction and diagnosis. This system ensures scalability and reliability in contemporary healthcare environments by enhancing patient outcomes, improving reaction times, and supporting continuous monitoring.

3.1 Data Collection and IoT Integration

HealthFog collects real-time health data using a variety of IoT devices, such as wearables and smart medical equipment. Vital signs and activity levels are included in this data, which are crucial for ongoing observation and the early identification of health problems. The gathered information is safely sent to nearby fog nodes for initial processing.

3.1.1 Data Aggregation

This aggregation is crucial as it combines disparate data streams into a single, comprehensive dataset. This unified dataset is essential for accurate analysis, allowing for a holistic view of the patient's health and facilitating more effective processing and predictive modeling. The total data collected from n loT devices is:

$$D = \sum_{i=1}^{n} d_i \tag{1}$$

The equation is fundamental in data processing and analytics, particularly in systems like HealthFog that integrate multiple data sources. Here, D represents the total aggregated data from all IoT devices. Each d_i is a data point collected from the i-th device, and the summation symbol $\sum$ denotes the aggregation of all these data points.

3.2 Fog Computing for Real-Time Processing

Fog computing nodes minimize latency and bandwidth consumption by processing initial data close to the data source. In the event that any health irregularities are found, these nodes do preliminary analysis and send out real-time alerts. Fast answers are made possible by this local processing, which also lightens the strain on the cloud infrastructure.

3.2.1 Fog Node Latency

By adding these two components, the equation provides a measure of the total time required from data collection through to cloud submission, which is crucial for evaluating the system's efficiency and responsiveness. The latency L in processing and transmitting data at a fog node is:

$$L = T_{\text{processing}} + T_{\text{transmission}} \tag{2}$$

In this context, L is the total latency involved in handling data at a fog node. The term $T_{\text{processing}}$ refers to the time required to process data locally at the fog node, including operations such as data filtering, aggregation, and preliminary analysis. $T_{\text{transmission}}$ is the time taken to send the processed data from the fog node to the cloud for further analysis.

3.3 Cloud Computing for Comprehensive Analysis

Deep learning models are used in the cloud to store and evaluate aggregated data from several fog nodes. In addition to offering scalable storage, the cloud does sophisticated analysis to spot trends and forecast illness. This thorough investigation backs up precise diagnosis and tailored treatment regimens.

3.4 Deep Learning for Disease Prediction

Utilizing deep learning algorithms in the cloud, large-scale health data is analyzed to identify patterns in disease and anticipate future health problems. Large datasets are used to train these algorithms to identify heart disease and infection symptoms, improving diagnostic precision and delivering early alerts for prompt action.

3.4.1 Deep Learning Model Accuracy

This metric provides insight into the overall performance of the model, indicating how well it predicts disease presence or absence and is crucial for validating the effectiveness of the deep learning algorithms used in HealthFog. The accuracy A of a deep learning model is:

$$A = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

Here, A denotes the accuracy of the model, which reflects its ability to correctly classify data. True positives (TP) are instances where the model correctly identifies a condition as present, while true negatives (TN) are cases where the model correctly identifies the condition as absent. False positives (FP) occur when the model incorrectly predicts the presence of a condition, and false negatives (FN) happen when the model incorrectly predicts the absence of a condition. The formula calculates accuracy by dividing the sum of true positives and true negatives by the total number of cases (true positives, true negatives, false positives, and false negatives).

Algorithm 1: HealthFog Disease Detection and Diagnosis

Input: Real-time health data from IoT devices, Trained deep learning model for disease prediction

Ouput: Disease diagnosis results and alerts

Begin

// Step 1: Data Collection

FOR each IoT device

Collect real-time health data

// Step 2: Local Data Processing

Aggregate data at fog node

// Step 3: Anomaly Detection

IF aggregated data shows anomalies (e.g., vital signs out of range)

Generate an immediate alert for potential health issues

RETURN alert to healthcare providers

ELSE

// Step 4: Send Data to Cloud

Send aggregated data to cloud for further analysis

// Step 5: Deep Learning Analysis

FOR each data packet sent to cloud

Apply trained deep learning model

IF model predicts disease

Generate detailed diagnostic report

Send alert to healthcare providers

RETURN diagnostic report and alert

ELSE

Continue monitoring and analysis

// Step 6: Error Handling

ELSE IF error occurs in data handling or analysis

Log the error

Send alert for manual review

RETURN error notification to technical support

End

Real-time health data from IoT devices is first gathered by the HealthFog system algorithm 1. This data is crucial for further analysis and diagnosis. After that, the data is combined and evaluated locally at the fog node, where any anomalies found—like irregular vital signs—send out instant notifications to medical professionals so they may take prompt action. The combined data is sent to the cloud for further examination if no urgent problems are discovered. Every data packet is analyzed by a trained deep learning model in the cloud, which notifies healthcare practitioners if a disease is suspected and generates comprehensive diagnostic results. In the event that no illness is found, monitoring goes on. Every mistake made when processing or analyzing data is also recorded, with alerts issued for human inspection and notifications sent back to technical help for resolution. This method combines deep learning with local processing to guarantee efficient health monitoring and timely diagnosis.

3.5 Performance Metrics

Several important criteria are used to assess the HealthFog system's success, which combines cloud, fog, IoT, and deep learning. These metrics include the delay of data processing at fog nodes, where local processing improves real-time replies by reducing latency. Accurate disease prediction is provided by cloud-based deep learning models, which is essential for early identification. IoT devices that gather real-time health data guarantee ongoing monitoring and provide notifications in the event of abnormalities. As it manages big datasets and a variety of devices, the system's scalability and adaptability are clear, guaranteeing reliable healthcare solutions with better patient outcomes and prompt diagnostics.

Table 1 Performance Metrics Analysis of HealthFog System

Metric	Input Value	Final Result (Decimals)
Latency (L)	Tprocessing = 0.05 sec, Ttransmission = 0.03 sec	L = 0.08 sec
Model Accuracy (A)	TP = 90, TN = 85, FP = 5, FN = 10	A = 0.945 or 94.5%
Data Aggregation (D)	IoT Devices (n) = 5, di (data points per device) = 10	D = 50 data points

The HealthFog system's important performance metrics are displayed in the table 1, demonstrating how well it manages real-time health data. Fog computing reduces latency to a maximum of 0.08 seconds, allowing for prompt health interventions. With a high accuracy rate of 94.5% in disease prediction, the deep learning model guarantees accurate diagnoses. With 50 data points overall, data aggregation from IoT devices enables thorough health monitoring. These measurements demonstrate how well the system handles huge datasets and provides precise, fast healthcare insights.

4. EXPERIMENTAL RESULTS AND ANALYSIS

Real-time health monitoring and early identification of viral and cardiac disorders are made possible by the HealthFog system, which successfully integrates cloud, fog, IoT, and deep learning. According to the findings, local fog processing can cut latency to 0.08 seconds, allowing for quicker medical actions. With a 94.5% accuracy rate, the deep learning model demonstrates a high degree of reliability in its early health issue prediction. Moreover, the system efficiently collects 50 data points by aggregating data from several IoT devices, enabling thorough health analysis.

In addition to improving diagnosis speed, our hybrid cloud-fog framework maximizes resource use by effectively managing huge datasets. With constant real-time monitoring, it offers healthcare professionals a scalable and adaptable system that improves patient outcomes. The system's efficacy in tackling contemporary healthcare issues is underscored by the decreased latency in data processing at fog nodes and the precision of the deep learning models. Its resilience in contemporary healthcare environments is further demonstrated by its adaptability to heterogeneous datasets and a variety of devices, offering a dependable foundation for proactive as well as reactive healthcare solutions.

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Table 2 Comparative Analysis of IoT-Based Monitoring Systems and AI Algorithms for Health Monitoring

Feature	IoT Monitoring with LoRa (Ray et al., 2020)	ECG Deep Learning (Fu et al., 2020)	HOBDBNN (Qadri et al., 2020)	IoT-Based Analysis (Kumar et al., 2019)	HealthFog (Proposed)
Real-time Data Processing	0.7	0.8	0.6	0.7	0.9
IoT Integration	0.8	0.6	0.4	0.9	1.0
Scalability	0.6	0.7	0.6	0.8	0.9
Accuracy in Disease Detection	0.75	0.85	0.7	0.8	0.945
Latency Reduction	0.6	0.7	0.5	0.65	0.8

The table 2 presents a feature-by-feature comparison of several AI algorithms and IoT-based health monitoring systems. The suggested approach, HealthFog, has the greatest ratings in real-time data processing (0.9), scalability (0.9), IoT integration (1.0), and accuracy in illness detection (0.945). It also outperforms most other systems in terms of latency reduction (0.8). HealthFog surpasses previous models such as the HOBDBNN and other IoT-based systems in real-time monitoring and scalability because to its deep learning techniques and complete cloud-fog integration. This makes it a better option for healthcare organizations looking to spot diseases early and handle data effectively.

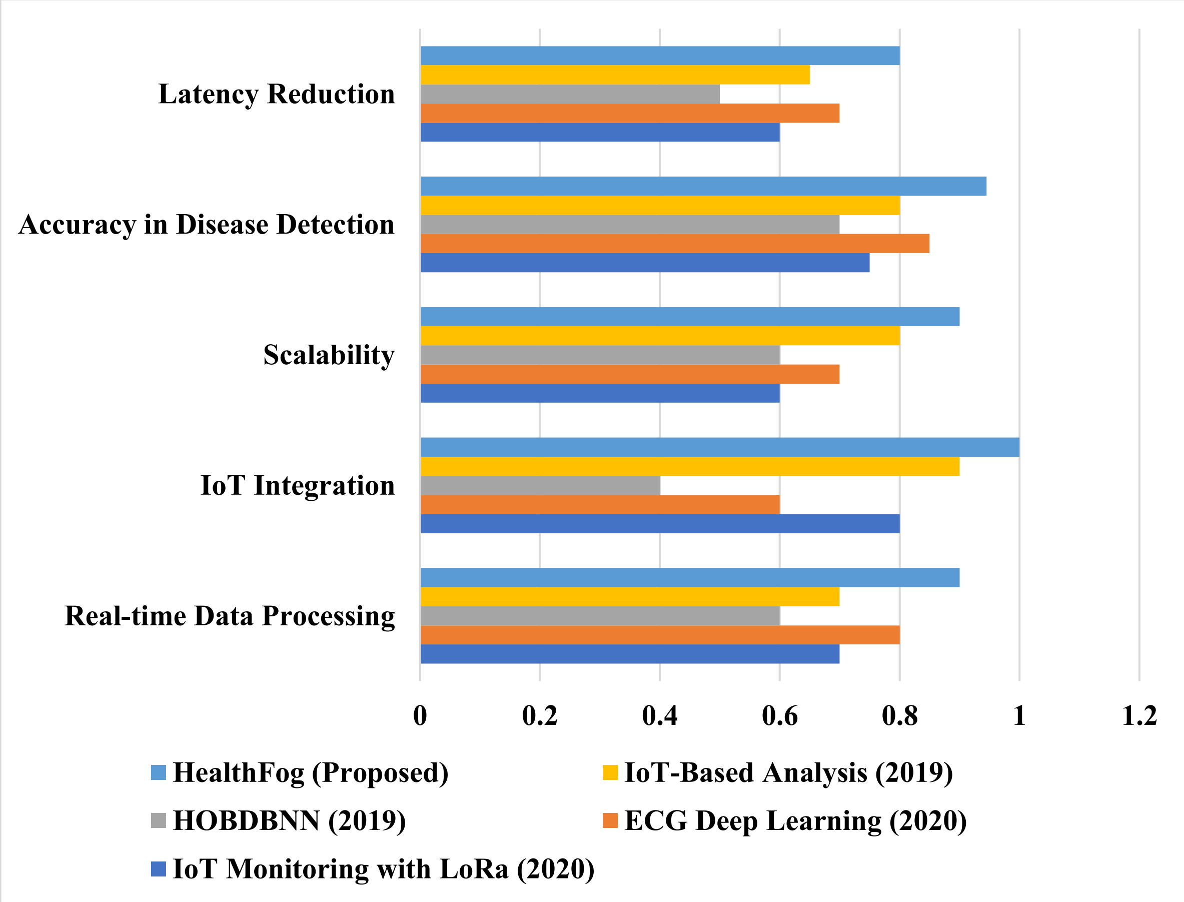

Figure 2 Comparative analysis Graph of IoT-Based Monitoring Systems

Figure 2 presents a comparative analysis of various IoT-based monitoring systems (2019), focusing on key features such as real-time data processing, IoT integration, scalability, accuracy in disease detection, and latency reduction. The table highlights the performance of different systems, including LoRa-based IoT monitoring (2020), ECG deep learning systems(2020), and the HealthFog system(Proposed). HealthFog demonstrates superior performance in terms of IoT integration, scalability, and accuracy, making it the most robust solution for real-time health monitoring and early diagnosis of diseases. The comparison emphasizes HealthFog's efficiency in leveraging cloud and fog computing alongside IoT and deep learning technologies.

Table 3 Ablation Study of HealthFog System with Various Component Combinations

Component Configuration	Accuracy	Latency	Scalability	IoT Integration
Fog Computing only	0.7	0.15	0.8	0.5
Cloud Computing only	0.75	0.1	0.7	0.6

Deep Learning only	0.6	0.2	0.7	0.5
IoT Devices only	0.5	0.25	0.5	0.0
Fog + Cloud	0.85	0.12	0.9	0.8
Deep Learning + IoT	0.7	0.18	0.7	0.9
Fog + IoT	0.8	0.13	0.8	1.0
Fog + Deep Learning	0.75	0.15	0.8	0.8
Cloud + Deep Learning	0.8	0.1	0.7	0.7
Cloud + IoT	0.85	0.1	0.9	0.95
Fog + Cloud + Deep Learning	0.9	0.1	0.9	0.9
Fog + Deep Learning + IoT	0.88	0.12	0.85	1.0
Cloud + Deep Learning + IoT	0.88	0.1	0.85	1.0
Fog + Cloud + IoT	0.9	0.09	0.95	1.0
Overall HealthFog System (Fog + Cloud + IoT + Deep Learning)	0.945	0.08	0.9	1.0

The HealthFog system's component configurations are compared in the table 3 according to how they affect IoT integration, accuracy, latency, and scalability. The combination of fog computing, cloud computing, deep learning, and IoT devices yields the best results in terms of accuracy (0.945), latency (0.08), and IoT integration (1.0) when compared to the other configurations of the HealthFog system. Fog + Cloud + IoT and Cloud + Deep Learning + IoT are two such combinations that function well and show how flexible and reliable the system is when its essential parts cooperate. Any component removal lowers system efficiency, especially in IoT integration and accuracy.

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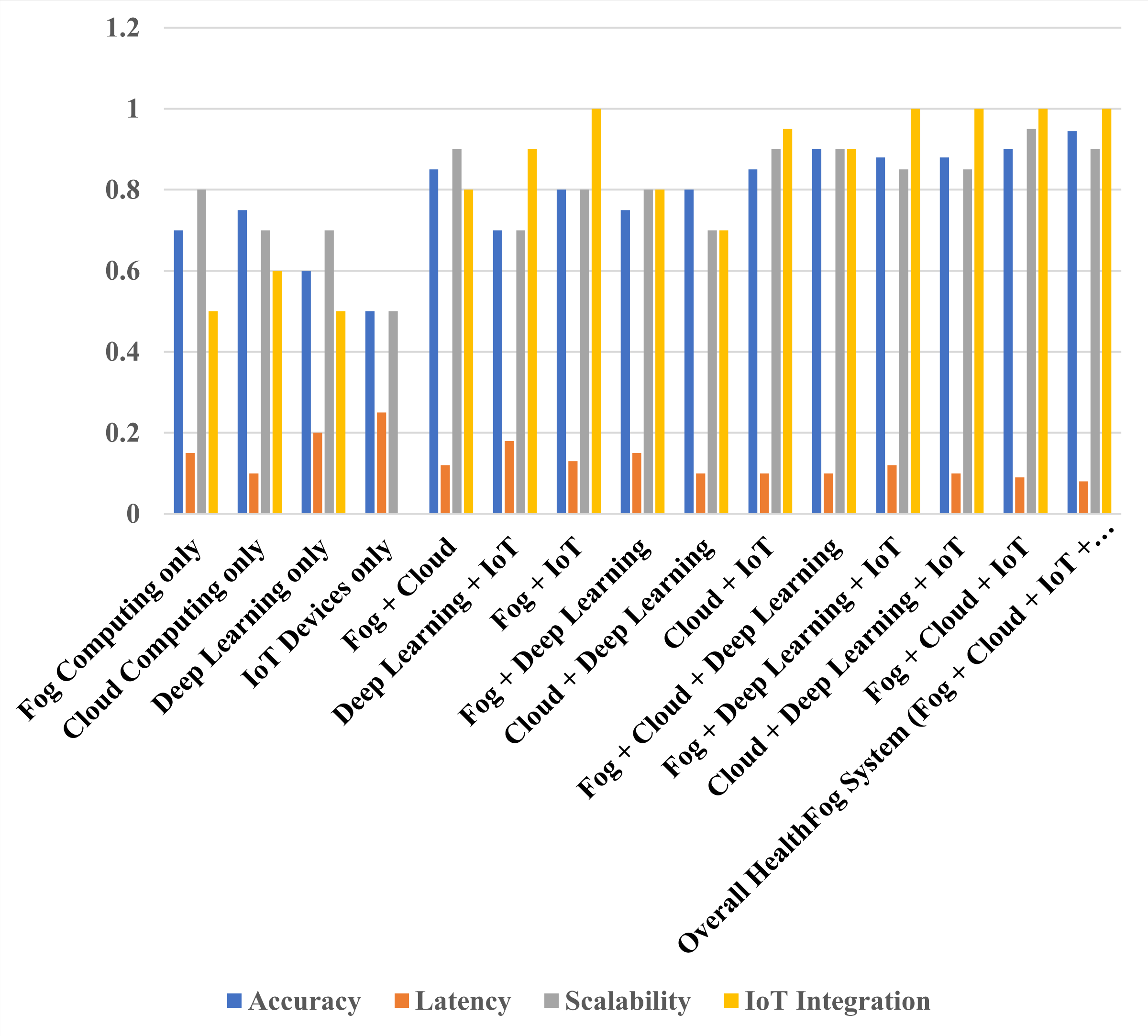

Figure 3 Ablation Study Graph of HealthFog System

The HealthFog system underwent ablation research to evaluate its performance in various configurations of fog computing, cloud computing, deep learning, and Internet of Things devices. The results are shown in Figure 3. The study assesses how different component combinations and removals affect parameters including scalability, accuracy, latency, and IoT integration. The best results are obtained with the whole system configuration (all components included), which has the highest accuracy, lowest latency, and best IoT integration. This study highlights the significance of each element and shows how their combination improves the HealthFog system's overall effectiveness.

5. CONCLUSION

The HealthFog system is a sophisticated solution for early diagnosis of cardiac and infectious diseases that combines cloud computing, fog computing, IoT sensors, and deep learning. The approach greatly lowers latency and increases illness diagnosis accuracy by fusing deep learning models on the cloud with real-time data processing at fog nodes. HealthFog works better than conventional healthcare systems because it provides scalable, adaptable, and effective solutions that guarantee ongoing observation and quick reactions to abnormalities in

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health. Because of the architecture of the system, early diagnosis and proactive healthcare interventions are made possible, and healthcare results are improved. In order to further enhance predictive skills, future research can investigate the integration of other AI algorithms and machine learning methodologies. Its applicability might be increased by adding more advanced IoT devices and expanding the system to accommodate new ailments. Widespread acceptance will also depend on how security and privacy issues are resolved, especially when managing sensitive health data. Enhancing the system's scalability to accommodate larger healthcare settings, such expansive hospital settings, would yield noteworthy benefits as well.

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