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DEVELOPMENT OF IOT OPTIMIZATION SYSTEM IN HEALTHCARE USING FEDERATED LEARNING

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ABSTRACT

The increasing adoption of Internet of Things (IoT) technologies in healthcare has enabled continuous monitoring of patients' physiological conditions through interconnected sensors and medical devices. However, conventional cloud-based healthcare IoT systems face challenges relating to latency, communication overhead, energy consumption, data privacy, device heterogeneity and Quality of Service (QoS). This study developed an IoT optimization system in healthcare using Federated Learning (FL) to support decentralized and privacy-preserving processing of healthcare data. The system was designed around local data preprocessing and model training at IoT devices, device selection based on available resources, and global model aggregation using the Federated Averaging (FedAvg) algorithm. A Hybrid Agile–Incremental development approach was adopted. The implementation used Python, Django, SQLite and machine-learning libraries identified in the thesis. Simulated healthcare sensor records containing physiological and device-related parameters were used for testing, and the model was trained with an 80:20 training–testing split. Evaluation of the binary global model, using a confusion matrix reported for 1,000 records, produced an accuracy of 93%, precision of 70%, recall of 78%, F1-score of 74%, false-positive rate of 5%, false-negative rate of 22% and negative predictive value of 96%. Functional tests also showed successful device connection, sensor-data handling, local training, model-update transmission, aggregation, authentication checks and dashboard access. The comparative assessment of the centralized and proposed federated models was qualitative: the thesis did not report direct numerical measurements for latency, energy consumption, communication overhead or QoS. The study demonstrates the implementation of a healthcare IoT monitoring framework that keeps raw patient data at local devices while coordinating model updates through federated learning.

KEYWORDS: Internet of Things, Healthcare, Federated Learning, IoT Device Optimization, FedAvg, Data Privacy, Quality of Service.

1. INTRODUCTION

The Internet of Things (IoT) has transformed healthcare monitoring by connecting sensors, wearable devices and medical equipment that collect and communicate patients' physiological information. In healthcare environments, these technologies support continuous monitoring of parameters such as heart rate, body temperature, blood pressure and oxygen saturation. The Internet of Medical Things (IoMT) therefore provides opportunities for remote patient monitoring, timely detection of abnormalities and improved healthcare service delivery (Elayan et al., 2021; Ali et al., 2022; Abbas et al., 2023).

Despite these benefits, conventional healthcare IoT systems commonly depend on centralized cloud architectures. Sensor readings are transmitted to cloud servers for storage, processing and analysis. This arrangement offers centralized computing and storage capabilities, but continuous transmission can increase communication delays, bandwidth use and device energy consumption. It also exposes sensitive patient information to risks associated with transmission and centralized storage (Kairouz et al., 2021; He et al., 2023; Aminifar et al., 2024).

Federated Learning (FL) provides a decentralized approach in which participating devices train models using their local datasets and communicate model updates to a coordinating server rather than sharing raw data. The server aggregates the updates to produce a global model, which is returned to participating devices for subsequent training. This approach is relevant to healthcare because it supports collaborative learning while keeping sensitive patient data at the point where it is generated (Rieke et al., 2020; Kairouz et al., 2021; Abbas et al., 2023).

However, FL does not remove every resource challenge. Repeated local training and model-update communication can still place demands on device energy, processing capacity and network resources. Healthcare IoT devices also differ in hardware capabilities and network conditions. Consequently, device-level optimization is important to ensure that FL participation and healthcare monitoring remain efficient (He et al., 2023; Aminifar et al., 2024).

The problem addressed in this study is the limited integration of privacy-preserving learning with device-level optimization in healthcare IoT systems. The study therefore developed an IoT optimization system in healthcare using FL. The system was intended to support local

processing, adaptive device participation and global model aggregation while addressing data privacy, communication efficiency and system responsiveness.

The specific objectives were to:

1. Design an IoT optimization system in healthcare integrated with Federated Learning to support decentralized and privacy-preserving data processing.
2. Develop an intelligent IoT device optimization mechanism that selects and manages devices based on energy level, computational capacity and network conditions.
3. Implement the Federated Learning process, including local model training on IoT devices and global model aggregation using Federated Averaging (FedAvg).
4. Evaluate the proposed system using simulation metrics including latency, energy consumption, communication overhead and Quality of Service (QoS).

The contribution of the study is the development of a healthcare IoT framework that combines local patient-data processing, federated model training and device-oriented optimization within one system.

2.0 RELATED LITERATURE

2.1 IoT-Based Healthcare Monitoring

IoT-based healthcare monitoring systems use connected sensors and medical devices to collect physiological information and make it available for remote observation. Ali et al. (2022) discussed IoT technologies for healthcare monitoring and the role of interconnected sensors in supporting patient care. Elayan et al. (2021) reviewed IoT applications in healthcare and identified scalability as an important concern as the number of connected devices increases. Wang (2024) examined wearable medical devices for remote monitoring and noted the importance of protecting patient information transmitted to centralized servers. These studies establish the value of continuous monitoring while highlighting the need for scalable and privacy-aware architectures.

2.2 Machine Learning and Edge–Cloud Healthcare Systems

Machine learning has been applied to healthcare data to support classification, prediction and clinical decision-making. Patro and Padhy (2023) developed an IoT cloud-based health-monitoring approach that used machine-learning techniques for heart-disease prediction. Their work is the existing system adopted for analysis in this study. The approach collects physiological data through sensors and transmits the data to a cloud environment for processing. Edge computing offers an alternative by moving some processing closer to the

data source. Zhang and Su (2022) examined Edge AI in IoT healthcare monitoring, while Hennebelle et al. (2025) considered an edge–cloud collaborative healthcare system. These works demonstrate the relevance of distributing computation between devices, edge resources and cloud infrastructure.

2.3 Federated Learning in Healthcare

Federated Learning allows multiple clients to train a shared model without centralizing their raw datasets. Rieke et al. (2020) discussed FL for digital health, while Kairouz et al. (2021) reviewed advances and open problems in federated learning. McMahan et al. (2017) introduced the communication-efficient Federated Averaging approach, in which local model updates are combined at a central server using a weighted average. In healthcare IoT, this arrangement is relevant because patient information can remain on local devices while model knowledge is shared through updates.

2.4 Optimization and Research Gap

Optimization is important because healthcare IoT devices operate with different processing capabilities, battery levels and network conditions. He et al. (2023) addressed federated learning under heterogeneous resource conditions, while Aminifar et al. (2024) examined energy-efficient FL for IoT-based healthcare systems. Sattler et al. (2020) considered communication-efficient federated learning, and Liu et al. (2023) examined resource allocation for IoT-enabled healthcare systems. The reviewed studies inform the need to consider privacy, device resources and communication together. In the thesis, the identified gap is the limited integration of FL with intelligent device optimization in a practical healthcare IoT system.

3.0 METHODOLOGY

3.1 Research and Development Approach

The study adopted an Agile–Incremental development methodology, described in the thesis summary as a Hybrid Agile–Incremental model. The approach was selected because the system contains separate components, including IoT device data acquisition, preprocessing, local model training, federated aggregation, optimization functions and a healthcare dashboard. The Agile aspect supports iterative refinement, while the incremental aspect enables modules to be developed and tested progressively before integration.

3.2 Existing-System Analysis

The existing system examined was the secure IoT cloud-based remote health-monitoring approach by Patro and Padhy (2023). In the architecture described in the thesis, IoT sensors

collect patient physiological data and transmit the readings through a communication network to a centralized cloud platform. Machine-learning and data-analytics processes are executed at the cloud layer, and results are made available through a healthcare dashboard or mobile application.

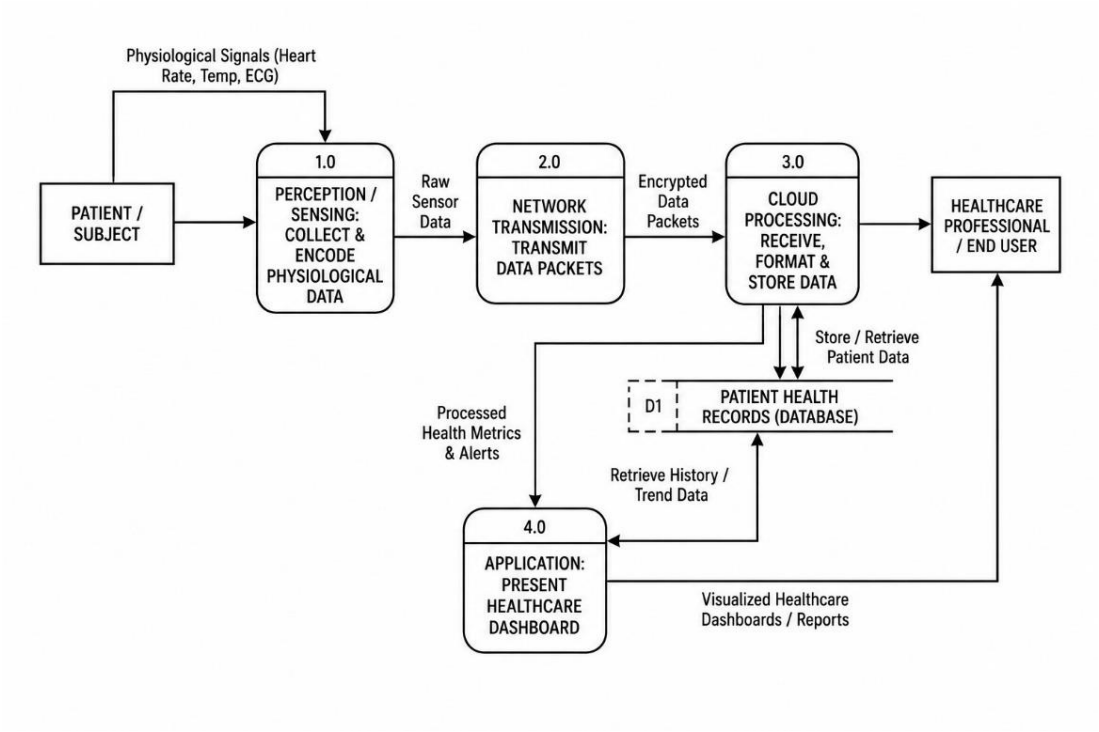


Figure 1. Data-flow diagram of the existing centralized healthcare IoT system.

The existing architecture supports continuous patient monitoring, centralized storage and cloud-based analytics. The thesis identifies its limitations as communication-related latency, energy use arising from continuous data transmission, privacy exposure during transmission and centralized storage, network bottlenecks and scalability concerns.

3.3 Proposed Federated Learning-Based System

The proposed system replaces the routine transfer of raw patient data to a central server with local processing and federated model training. Patient IoT devices collect physiological readings and perform local preprocessing, including data cleaning, validation, normalization and feature extraction. Local models are trained using device-held data. The devices transmit model updates rather than raw patient records, and the federated server aggregates the updates using FedAvg. The updated global model is redistributed to participating devices.

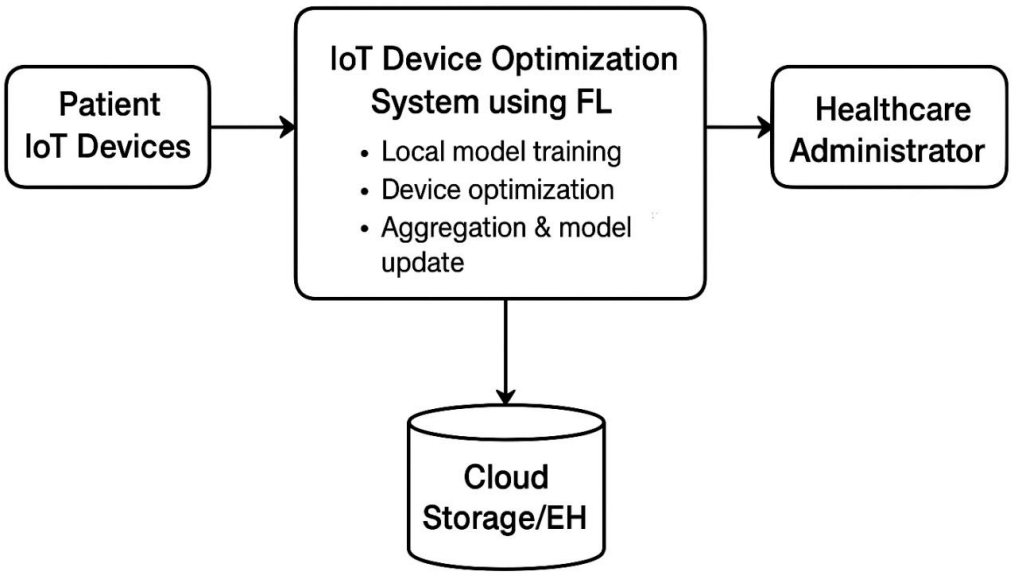


Figure 2. Data-flow context diagram of the proposed IoT optimization system using Federated Learning.

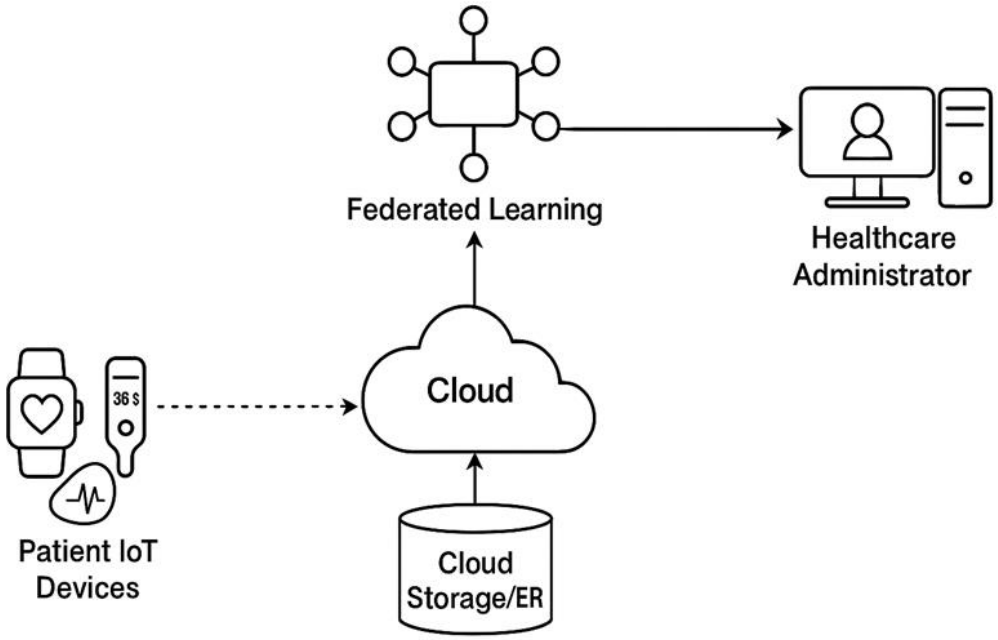


Figure 3. System architecture of the proposed healthcare IoT and Federated Learning framework.

3.4 Federated Learning and Device-Optimization Workflow

The workflow described in the thesis begins with initialization of the global model at the FL server and registration of IoT devices. The optimization engine evaluates device information,

including battery, computational and network-related conditions, and selects devices for a training round. The server distributes the current global model to selected devices. Each device preprocesses its local patient data and trains the model locally. Model updates are secured and transmitted to the server, where FedAvg is used to aggregate the updates. The global model is then updated and redistributed, and the process is repeated.

Stage	Operation reported in the thesis
1	Initialize the global model and register IoT devices.
2	Collect device metrics and select eligible devices for the FL round.
3	Distribute the global model to selected devices.
4	Collect and preprocess local patient sensor readings.
5	Train the local model using each device's private dataset.
6	Secure and transmit model updates; raw patient data remain local.
7	Aggregate updates at the server using FedAvg and redistribute the updated global model.
8	Update dashboard analytics and repeat the optimization and FL round.

3.5 Data and Model Evaluation

The thesis describes simulated healthcare IoT sensor records containing device identifier, heart rate, SpO_2, body temperature, systolic and diastolic blood pressure, respiration rate, battery level, signal strength and timestamp. A sample of 50 sensor records is presented in the thesis. The model was trained using 80% of the dataset, while 20% was reserved for testing. The global model was evaluated as a binary classifier, with normal readings represented by 0 and abnormal events represented by 1. The reported confusion matrix was based on 1,000 records.

The evaluation measures reported in the thesis were precision, recall (sensitivity), accuracy, F1-score, false-positive rate (FPR), false-negative rate (FNR) and negative predictive value (NPV).

4.0 SYSTEM DESIGN AND IMPLEMENTATION

4.1 Implementation Environment

The system was implemented using Python and the Django web framework. SQLite was identified as the database tool, while PyCharm was used as the Python editor. The software requirements listed in the thesis also include Windows 10, Scikit-learn (sklearn), Pillow, joblib and HTML. The application provides functions for user login, device registration, patient registration, recording vital signs, viewing patient records and viewing predictive reports.

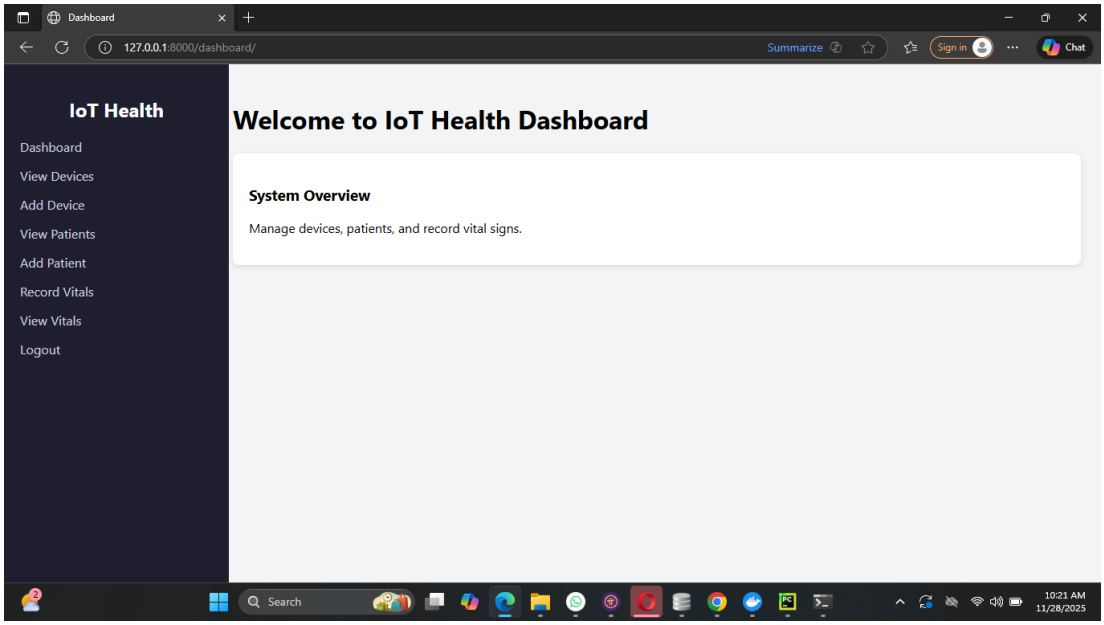


Figure 4. Main dashboard interface of the implemented IoT healthcare system.

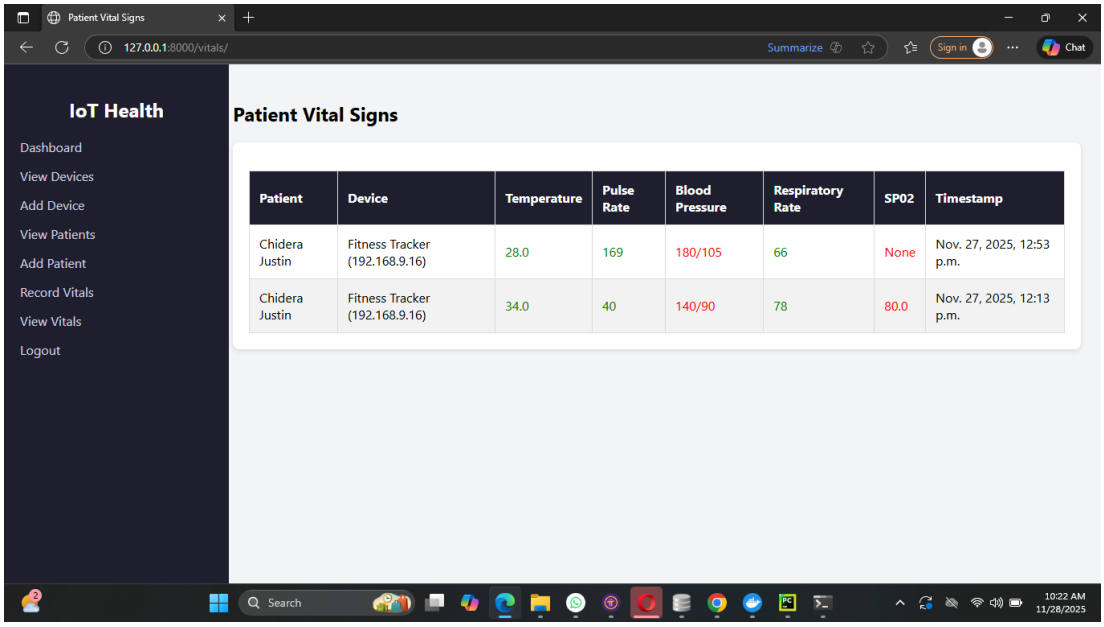


Figure 5. Patient vital-signs interface of the implemented system.

4.2 Data Handling and Functional Modules

The database structures described in the thesis include user, IoT device, patient and vital-sign records. The vital-sign record structure includes temperature, pulse rate, blood pressure, respiratory rate, SpO_2, timestamp, device identifier and patient identifier. The main system functions cover device registration, patient registration, recording vital signs, local model training, model-update transmission, FL aggregation and display of analytics through the dashboard.

4.3 Federated Aggregation

Federated Averaging is the aggregation technique specified for the proposed system. Each participating device trains a local model and submits its updated parameters. The server combines the updates to form the global model and redistributes the result for subsequent training rounds. The thesis describes this as the central coordination step that supports collaborative learning without centralizing raw patient data.

5.0 TESTING AND RESULTS

5.1 Functional Testing

Testing covered device connection, sensor-data transmission and storage, local model training, model-update transmission, server aggregation, application of the updated model, authentication failure, network failure, data-integrity checking and dashboard access. The actual outcomes reported in the thesis are summarized in Table 1.

Test description	Actual result reported
IoT device connection	Device authenticated and connected successfully.
Sensor-data transmission	Data received in the correct format and validated.
Server parsing and storage	Data stored correctly in the database.
Local model training	Local model trained successfully.
Model-update upload	Update received and verified by the FL server.
FL aggregation	Global model updated successfully.
Applying updated model	Optimized model applied successfully.
Authentication failure	Unauthorized device was blocked.
Network failure	Data queued and resent when network was restored.
Data integrity	Corrupted data flagged and rejected.
Dashboard access	Dashboard displayed the correct metrics.

5.2 Confusion Matrix and Classification Results

The confusion matrix reported for the final global model is presented in Table 2. It contains 820 true negatives, 45 false positives, 30 false negatives and 105 true positives, giving 1,000 evaluated records.

Table 2. Confusion matrix of the final global model.

Actual class	Predicted: Normal (0)	Predicted: Abnormal (1)
Normal (0)	820	45
Abnormal (1)	30	105

Table 3. Summary of classification performance.

Evaluation metric	Reported value
Precision	70%
Recall (Sensitivity)	78%
Accuracy	93%
F1-score	74%
False-positive rate (FPR)	5%
False-negative rate (FNR)	22%
Negative predictive value (NPV)	96%

The reported results indicate that the global model correctly classified 925 of the 1,000 records, comprising 820 normal readings and 105 abnormal readings. The reported accuracy was 93%. Precision was 70%, while recall was 78%, indicating the proportion of actual abnormal events identified by the model. The F1-score was 74%. The negative predictive value was reported as 96%, meaning that most readings classified as normal were normal according to the confusion matrix.

5.3 Comparative Assessment of Existing and Proposed Models

The thesis compares the existing centralized model and proposed federated model using latency, energy consumption, communication overhead and QoS. The comparison is qualitative, as the thesis explicitly states that direct numerical measurements for these four system-level metrics were not obtained. Table 4 retains the nature of the comparison reported in the thesis.

Table 4. Qualitative comparison of the existing and proposed models.

Performance parameter	Existing centralized model	Proposed federated model
Latency	May experience additional communication delays because patient data must be transmitted to the cloud for processing.	Local training reduces the need to transmit raw patient data for every training operation and may reduce communication-related delays.
Energy consumption	Frequent data transmission and dependence on cloud communication may increase IoT-device energy demand.	Local processing and reduced raw-data transmission may reduce communication energy consumption.
Communication overhead	Requires transmission of patient data from IoT devices to the central server.	Transmits model updates instead of raw patient data during federated training.
Quality of Service (QoS)	May be affected by network availability, communication delays and dependence on the central server.	Local processing and distributed training may improve responsiveness and privacy, depending on device resources, network conditions and aggregation performance.

6.0 DISCUSSION

The system design combines healthcare IoT data acquisition with local preprocessing, device participation and federated model aggregation. In contrast to the existing centralized architecture examined in the thesis, the proposed approach keeps raw patient readings at the local devices and communicates model updates for global aggregation. This is the principal privacy-preserving distinction between the two architectures.

The functional test results show that the principal system operations described in the thesis were completed successfully. Devices connected, sensor readings were received and stored, local training was performed, model updates were received by the FL server, and the global model was updated. The tests also reported that unauthorized devices were blocked, corrupted data were rejected, and queued data were resent after network restoration.

The classification results provide a numerical assessment of the global model. The model achieved 93% accuracy, with 70% precision, 78% recall and a 74% F1-score. The confusion matrix also shows 45 false positives and 30 false negatives. These results indicate that the classifier identified both normal and abnormal readings, although the precision and recall values show that classification errors remained.

An important distinction concerns the system-level optimization objectives. Although the proposed architecture is designed to reduce latency, energy consumption and communication overhead and to improve QoS, the comparative table in the thesis is qualitative. It does not report measured numerical values for these four parameters. Consequently, the classification results should not be interpreted as direct quantitative proof of latency reduction, energy savings or QoS improvement. These outcomes remain architectural expectations in the reported comparison and require direct measurement in further evaluation.

7.0 CONCLUSION

This study developed an IoT optimization system in healthcare using Federated Learning. The proposed framework combines healthcare IoT devices, local data preprocessing and model training, device selection based on resource conditions, and global model aggregation using FedAvg. The system was implemented using Python, Django and SQLite, with the supporting software components identified in the thesis.

Functional testing reported successful operation of the major system processes, including device connection, sensor-data handling, local training, model-update transmission, global aggregation, authentication checks, data-integrity checking and dashboard access. The final global model achieved 93% accuracy, 70% precision, 78% recall, 74% F1-score, 5% FPR, 22% FNR and 96% NPV. The study therefore demonstrates the feasibility of integrating federated learning into a healthcare IoT monitoring application while keeping raw patient data local.

The study’s comparative assessment of latency, energy consumption, communication overhead and QoS was qualitative rather than numerical. Further evaluation should therefore

directly measure these parameters under controlled conditions, consistent with the recommendation and limitations stated in the thesis.

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