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Smart Based IoT Optimization Framework using Federated Learning (FL) Approach for Healthcare

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Abstract - The healthcare sector is increasingly leveraging Internet of Things (IoT) technologies to enable real-time patient monitoring, predictive diagnostics, and personalized treatment. However, the large volume of heterogeneous data generated by IoT devices poses challenges in data processing, accuracy, and timely decision-making. This study proposes an IoT optimization system using machine learning (ML) to enhance the efficiency and reliability of healthcare monitoring systems. The framework integrates wearable sensors, smart medical devices, and cloud/edge computing platforms to collect and preprocess physiological and environmental data from patients. These devices generate large volumes of sensitive patient data that require secure, efficient, and privacy-preserving analytics. Conventional cloud-based machine learning approaches often expose raw data to centralized servers, creating significant challenges in terms of data privacy, network congestion, latency, and compliance with healthcare regulations. To address these challenges, this thesis proposes an IoT Device Optimization System using Federated Learning (FL) for intelligent, distributed data processing and device performance enhancement in a healthcare environment. A hybrid Agile–Incremental development methodology was adopted to support iterative prototyping, modular expansion, and continuous validation. Comprehensive testing including unit, integration, system, and performance evaluation demonstrated that the proposed system improves prediction accuracy, minimizes data exposure risk, and enhances device responsiveness. The results show that FL-enabled optimization improves model accuracy (93%), and maintain strict privacy standards. This thesis contributes a scalable, secure, and intelligent framework for optimizing healthcare IoT devices, supporting remote diagnostics, smart clinical environments, and personalized healthcare delivery.

Keywords: Machine Learning, Federated Learning (FL) for Healthcare, IoT based optimization System

I. INTRODUCTION

The healthcare sector is increasingly adopting digital technologies to improve the quality, accessibility, and efficiency of medical services. One of the most transformative innovations in this domain is Remote Patient Monitoring (RPM), which enables continuous observation of patients' health conditions outside traditional clinical settings. RPM relies heavily on the Internet of Things (IoT), where wearable devices, biomedical sensors, and smart medical equipment collect real-time physiological data such as heart rate, blood pressure, oxygen saturation, body temperature, and glucose levels, and transmit them to healthcare providers for analysis and intervention. IoT-based remote patient monitoring has become particularly important in managing chronic diseases, elderly care, post-operative follow-up, and infectious disease control. By allowing clinicians to monitor patients remotely, RPM reduces hospital visits, lowers healthcare costs, and improves patient comfort and outcomes [1]. The COVID-19 pandemic further accelerated the adoption of remote monitoring solutions, highlighting the need for scalable and intelligent healthcare systems capable of continuous, real-time patient surveillance [2]. However, the effectiveness of IoT-based RPM systems is limited by several technical and operational challenges. These systems generate massive volumes of heterogeneous data at high velocity, which traditional rule-based or manual analysis methods cannot efficiently process. As a result, healthcare providers often face issues such as delayed diagnosis, false alarms, missed critical events, and inefficient use of medical resources [3]. Additionally, sensor noise, data redundancy, energy constraints of wearable devices, and network latency further degrade system performance. To overcome these challenges, Machine Learning (ML) has emerged as a powerful tool for optimizing IoT-based remote patient monitoring systems. Machine learning algorithms can learn from historical and real-time patient data to identify patterns, predict health deterioration, classify medical conditions, and detect anomalies automatically. For example, ML models can be used to predict cardiac abnormalities, detect early signs of respiratory failure, or forecast hospital readmissions based on continuous sensor data [4].

The integration of machine learning into IoT-based RPM systems enables intelligent optimization by improving data accuracy, reducing false alerts, enhancing predictive capabilities, and supporting personalized healthcare delivery. Furthermore, ML-driven optimization can improve system efficiency by prioritizing critical data, optimizing sensor usage, and enabling proactive clinical decision-making. Despite these benefits, many existing RPM solutions still lack robust optimization frameworks that fully exploit machine learning for real-time analytics, especially in resource-constrained healthcare environments. Therefore, there is a growing need for an optimized IoT-based remote patient monitoring system that leverages machine learning techniques to enhance data processing, predictive accuracy, and clinical responsiveness. Such a system has the potential to significantly improve patient safety, reduce healthcare costs, and support sustainable healthcare delivery in both developed and developing regions. This research is motivated by the need to bridge this gap by developing an IoT device optimization system that leverages machine learning in healthcare environments. Such a system aims to integrate privacy-preserving model training with strategies for improving device efficiency, extending battery life, and enhancing the quality of service across heterogeneous healthcare networks. By addressing both data privacy and device optimization simultaneously, the proposed approach seeks to contribute to the design of intelligent, secure, and sustainable IoT-based healthcare systems. Ultimately, this work has the potential to advance the next generation of healthcare technologies, enabling reliable real-time monitoring, safeguarding patient data, and ensuring that medical IoT devices operate effectively within the constraints of real-world environments. The objective of this paper was to: analyze the challenges associated with traditional IoT optimization techniques in healthcare environments, to design a Machine Learning-based optimization framework for healthcare IoT device management, to develop adaptive learning techniques that enhance the scalability and security of healthcare IoT networks, to optimize the performance of the IoT monitoring system by reducing false alarms and improving predictive accuracy and to evaluate the proposed system based on metrics such as accuracy, latency, reliability, and efficiency.

II. RELATED LITERATURE REVIEW

The rapid expansion of the Internet of Things (IoT) in healthcare has led to the emergence of the Internet of Medical Things (IoMT), a network of interconnected medical devices and applications that facilitate real-time patient monitoring, diagnosis, and treatment. While IoT adoption has created opportunities for personalized medicine, predictive analytics, and cost reduction, it also presents significant challenges such as privacy risks, data heterogeneity, energy constraints, and latency issues [5]. This paper reviews existing studies, frameworks, and methods related to IoT in healthcare, machine learning, knowledge extraction, and AI in healthcare.

[1] conducted a comprehensive survey of the state of the IoT (Internet of Things) in health care applications. The study systematically reviewed how IoT technologies are being applied across various healthcare domains, with a particular emphasis on architectures, network platforms, applications, challenges, and integration strategies within IoT enabled health systems. [6] conducted a seminal, comprehensive survey on the Internet of Things (IoT), laying the theoretical and architectural foundation for IoT as a global, interconnected ecosystem of physical objects. The paper maps the evolution of IoT from machine to machine (M2M) communication toward an integrated network of smart devices capable of sensing, communicating, and acting in distributed environments. [3] conducted a comprehensive review of how Internet of Things (IoT) technologies affect the healthcare industry, with a focus on improving clinical processes, patient management, and operational workflows. The study systematically surveyed existing research, IoT applications, and emerging trends in healthcare IoT deployment. The study by [7] provides a comprehensive review of deep learning applications for Electronic Health Record (EHR) data analysis. Over the past decade, digital adoption of EHR systems has dramatically increased the volume and complexity of clinical data available. While traditional machine learning methods have been applied to EHRs, the authors highlight a growing trend in using deep learning techniques to extract meaningful information from these datasets. [8] propose Health CPS, a healthcare cyber physical system designed to address the big data challenges in modern healthcare. As healthcare technologies evolve, vast amounts of data are generated at high

velocity from diverse medical devices, wearables, electronic health records, and clinical systems. This surge in heterogeneous data creates significant difficulties in storage, processing, and real time analysis. [9] investigate the security vulnerabilities of deep learning (DL) models used in COVID 19 diagnostic systems that rely on medical Internet of Things (IoT) devices. As medical IoT technologies including thermal cameras, radiological imaging (e.g., CT scans, X rays), face detection for social distancing, and mask detection systems have become integral to pandemic response, deep learning models are increasingly employed to automatically interpret sensor and image data. The authors demonstrate that these DL models remain susceptible to adversarial perturbations, where small, strategically crafted modifications to input data (known as adversarial examples) can mislead models into producing incorrect classifications. [10] provide a comprehensive guide to deep learning techniques and their applications in healthcare, focusing on how deep neural networks can transform key medical domains. The paper reviews major deep learning approaches including computer vision, natural language processing (NLP), reinforcement learning, and generalized deep learning methods and demonstrates how these techniques can be applied to enhance diagnostic accuracy, extract information from unstructured clinical data, and support complex medical decision tasks. [11] developed an IoT based remote monitoring system for patients with heart failure that integrates intelligent health monitoring, cloud computing, and machine learning techniques to facilitate continuous patient surveillance outside clinical settings. The study emphasizes how Internet of Medical Things (IoMT) technologies, including smart sensors and wireless communications, can transform traditional healthcare by enabling real time data collection on patient vital signs and activities. The authors proposed an intelligent framework that collects physiological data from individuals with heart conditions and uses a machine deep ensemble learning model (ET CNN) combining Extra Tree Classifier and Convolutional Neural Network architectures to predict the presence of cardiac disease and classify patients based on severity. [12] present a comprehensive survey on the integration of Ambient Intelligence (AMI) with the Internet of Medical Things (IoMT) to advance smart healthcare systems. Ambient Intelligence refers to computing environments that are adaptive, context aware, and responsive to human needs. The study explores how combining Artificial Intelligence (AI) with IoMT technologies can create intelligent healthcare ecosystems that continuously monitor and respond to patients' conditions. The paper reviews key components of IoMT infrastructure including both wearable and non-wearable medical devices, sensor networks, communication technologies, and data ecosystems that support AMI in healthcare settings. [13] investigates the application of Internet of Things (IoT) based remote patient monitoring (RPM) systems in the management of chronic diseases such as diabetes, cardiovascular disorders, and chronic obstructive pulmonary disease. The study explores how interconnected IoT devices including wearable sensors and smart medical equipment can collect real time physiological data (e.g., blood pressure, heart rate, oxygen saturation) from patients in their daily environments. [14] presents a comprehensive review of the integration between Machine Learning (ML) and the Internet of Things (IoT) within healthcare systems, with a particular focus on patient monitoring applications. The paper examines a wide range of IoT technologies including wearable sensors, embedded devices, and smart medical equipment that continuously collect real time physiological and behavioral data from patients. [15] present an IoT and Artificial Intelligence enabled framework for Remote Patient Monitoring (RPM) designed to overcome limitations in traditional healthcare services such as delays, high costs, and inconveniences associated with in person checkups. The study argues that advances in technologies like Cyber Physical Systems (CPS), 5G cellular networks, and IoT provide an opportunity to create intelligent healthcare use cases that improve patient outcomes. [16] propose an edge AI enabled Internet of Things (IoT) healthcare monitoring system designed for smart city environments, aiming to support real time patient monitoring, data analysis, and prompt clinical responses without relying solely on centralized cloud processing. The study presents a hybrid architecture combining IoT sensor networks, edge computing nodes, and artificial intelligence algorithms to collect and preprocess vital health data from wearable devices and ambient sensors.

III. METHODOLOGY

This paper follows a hybrid Agile–Incremental Model, which is suitable because the system involves advanced components (IoT, FL training, security

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modules, and cloud services) that must be built and tested in iterative cycles. The Hybrid Agile–Incremental methodology combines the flexibility and iterative feedback of Agile with the structured incremental delivery of the Incremental model. It is particularly suitable for complex systems where components can be developed, tested, and deployed in phased increments, but frequent stakeholder feedback and adaptability are also crucial. Agile focuses on iterative development, collaboration with stakeholders, and adapting to changes quickly. Incremental development delivers the system in smaller, fully functional increments, allowing for partial deployment and testing before the final system is complete.

Hybridization ensures both:

1. Flexibility to adapt to new requirements or design changes (Agile), and
2. Structured progression through modular system increments (Incremental).

Table 1: How hybrid Agile–Incremental Model Works in IoT FL Healthcare System

Phase	Agile Aspect	Incremental Aspect	Example in Project
Requirements	Frequent interaction with doctors/admins to refine data and privacy needs	Gather core system requirements first	Determine what patient vitals, devices, and privacy rules are needed
Design	Iteratively refine architecture and UML diagrams	Modular design for components	Device onboarding, local trainer, FL server designed separately
Development	Short sprints with working modules	Deliver partial functionality per increment	Sprint 1: device onboarding, Sprint 2: local training module
Testing	Continuous testing during sprints	Validate each increment independently	Unit test local trainer; integration test with server increment
Deployment	Pilot deployment for feedback	Deploy incrementally in controlled environments	First deploy onboarding + authentication; later deploy FL aggregation
Maintenance	Adapt system based on feedback	Extend incrementally with new modules or optimizations	Add device optimization module after initial deployment

IV. ANALYSIS OF THE EXISTING SYSTEM

The existing healthcare IoT system primarily relies on centralized data processing and cloud-based learning models for monitoring patients' physiological parameters such as heart rate, body temperature and oxygen saturation. In this architecture, IoT devices such as wearable sensors or smart medical monitors collect patient data and transmit it directly to a centralized cloud server where machine learning models are trained and updated. Although this setup allows for real-time monitoring and data storage, it suffers from several critical limitations, especially when dealing with large-scale healthcare environments or resource-constrained IoT devices.

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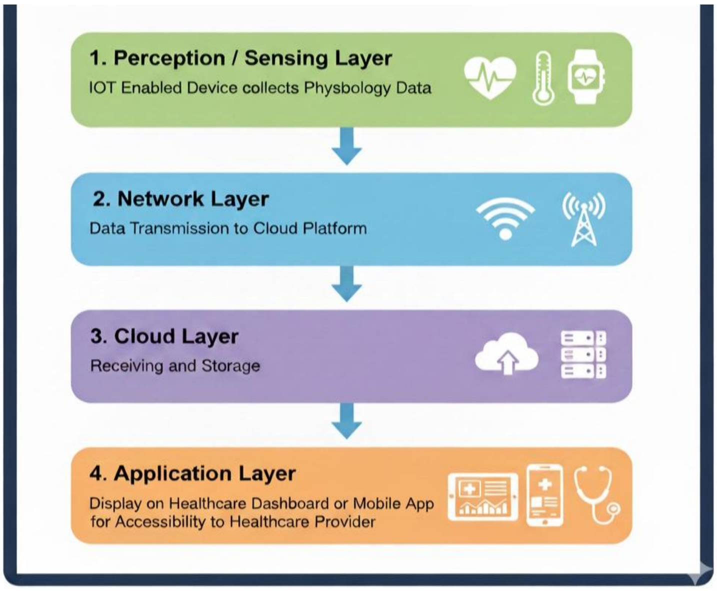

Figure 1: Data flow diagram of the existing system

V. THE PROPOSED SYSTEM DIAGRAM

The proposed system introduces a Federated Learning-based IoT optimization framework designed to address the limitations of traditional centralized healthcare systems. Instead of transmitting raw patient data to a central cloud server, the proposed architecture allows local IoT edge devices (such as wearable sensors and smart gateways) to train machine learning models locally and share only the model updates with a global federated server.
This decentralized approach significantly enhances privacy, reduces communication overhead, minimizes latency and optimizes energy usage, thereby improving the Quality of Service (QoS) in real-time healthcare monitoring.

The proposed system consists of the following major components:

1. IoT Devices (Edge Nodes): These include wearable healthcare devices such as heart rate sensors, temperature sensors and pulse oximeters that continuously collect patient vital signs. Each device performs local data processing and training using lightweight machine learning models.
2. Edge Gateway / Local Server: Serves as an intermediary node that aggregates local model updates from IoT devices within its range (e.g., a hospital ward, home or clinic). The gateway coordinates local training rounds and forwards the aggregated model to the global server for synchronization.
3. Federated Learning Server (Global Aggregator): The central server aggregates model updates from multiple edge gateways using techniques such as Federated Averaging (FedAvg). The updated global model is then redistributed to all participating edge nodes for the next training iteration.
4. Cloud Layer / Data Storage: The cloud layer store encrypted model parameters, manages global orchestration and supports additional analytics while maintaining strict privacy controls. No raw patient data is ever uploaded to the cloud.
5. Application Layer: Provides healthcare professionals with dashboards and real-time visualizations of patients' health parameters, anomaly alerts and predictive analytics for proactive care.

The System Workflow of the proposed system is as follows.

1. IoT devices collect physiological data (heart rate, body temperature, oxygen saturation).
2. Each device performs local preprocessing and feature extraction.
3. Local training of the model occurs using the device's dataset.
4. Model parameters (not raw data) are encrypted and sent to the edge gateway.

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5. The gateway performs local aggregation and forwards the updates to the federated learning server.
6. The global model is updated and redistributed to participating devices for another round of training.
7. The system continuously improves its accuracy while preserving privacy and minimizing communication load.

VI. DATAFLOW DIAGRAM OF THE PROPOSED SYSTEM

Below is a complete Data Flow Diagram (DFD) for IoT Device Optimization System Using Federated Learning (FL) in a Healthcare Environment. It is divided into three; DFD Level 0 (Context Diagram) and DFD Level 1 (Decomposition of Main Processes).

DFD Level 0 (Context Diagram)

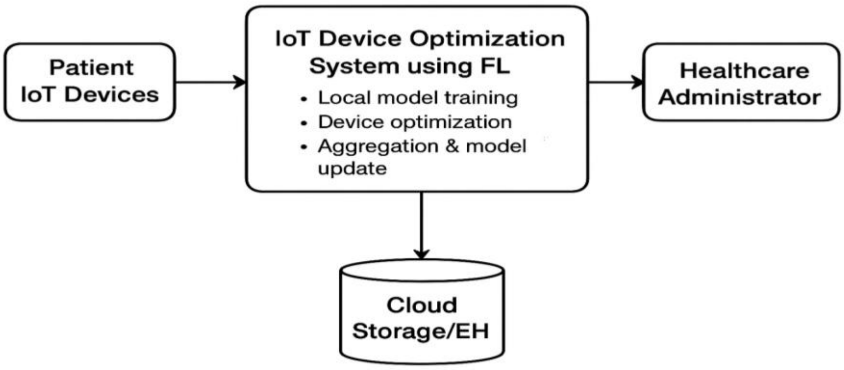

Figure 2: DFD Level 0 (Context Diagram)

From Figure 2 above shows the entire IoT Federated Learning System as a single high-level process interacting with external entities, the external entities are:

1. Patient IoT Devices: It send sensor data and receive updated model
2. Healthcare Administrator / Clinicians: View analytics & alerts and Manage system settings
3. Cloud Storage / HER: Stores historical model versions and Stores anonymized aggregated data

DFD Level 1 (Decomposition of Main Processes)

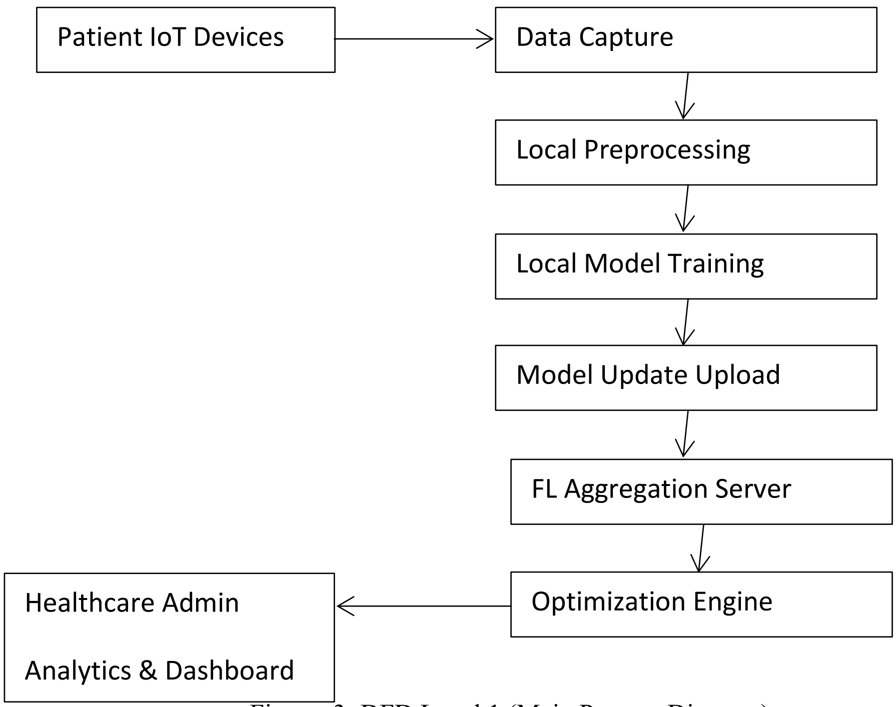

Figure. 3: DFD Level 1 (Main Process Diagram)

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SYSTEM ARCHITECTURE DIAGRAM

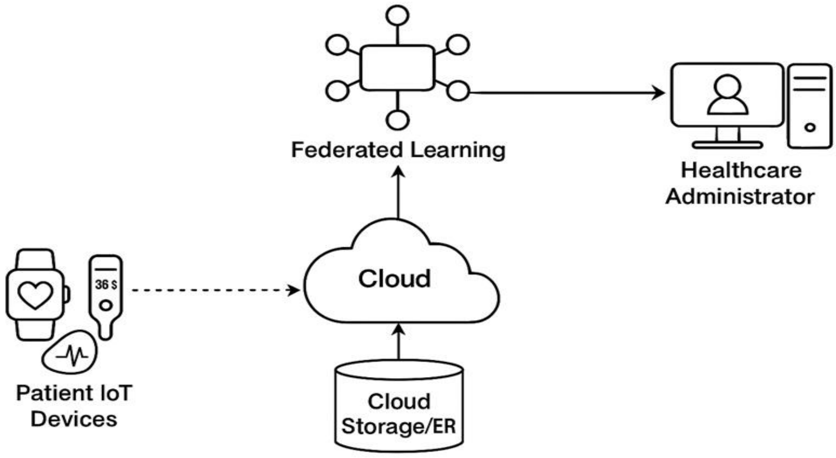

Figure 4: System architecture diagram

Figure 4 above illustrates how data flows and how different components interact in a healthcare-focused IoT system powered by Federated Learning (FL). The goal of the system is to optimize IoT device performance, improve health monitoring, and ensure privacy-preserving machine learning.

1. Patient IoT Devices (Edge Layer): These devices collect real-time physiological health data from patients. Continuously measure vital signs, process data locally, train local machine learning models (using FL) and send *only model updates/gradients* not raw health data to the cloud/FL server.
2. Cloud Server (Federated Learning Server): Acts as the central coordinator for Federated Learning. Send initial global model to devices and receive local model updates from devices. Perform secure aggregation (e.g., FedAvg) and update the global shared model.
3. Cloud Storage / Electronic Health Records (EHR): Used for storing aggregated results and allowing administrators to query patient trends without accessing raw device data
4. Healthcare Administrator Interface: A doctor or health analyst interacts with the system through a dashboard. They can view model performance, monitor patient trends, receive automated health alerts.

SEQUENCE DIAGRAM OF THE PROPOSED SYSTEM

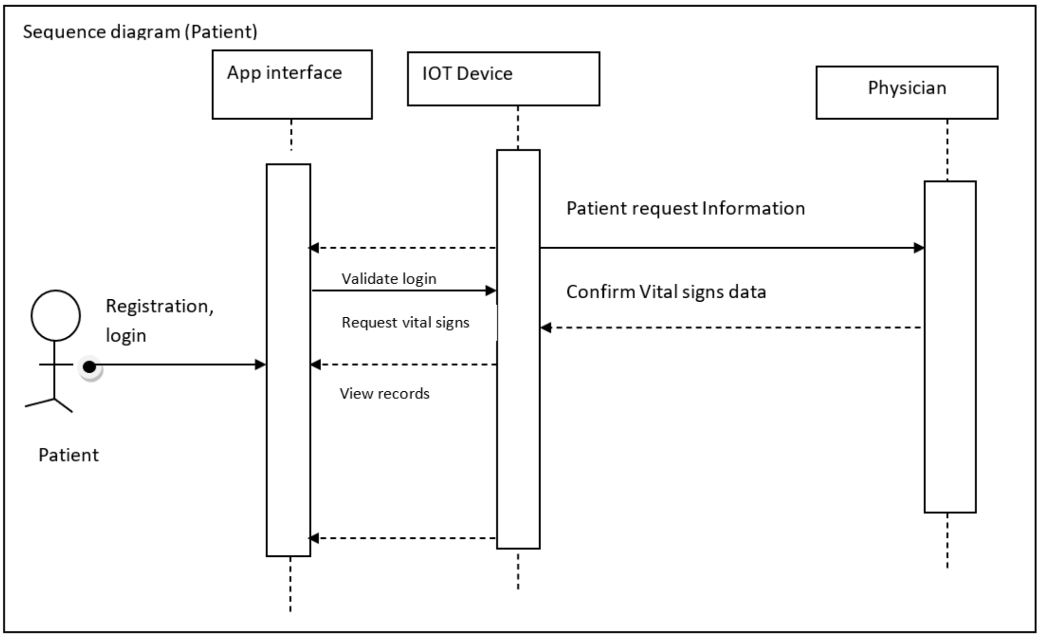

Figure 5: Sequence Diagram of Patient

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Sequence Diagram (Physician)

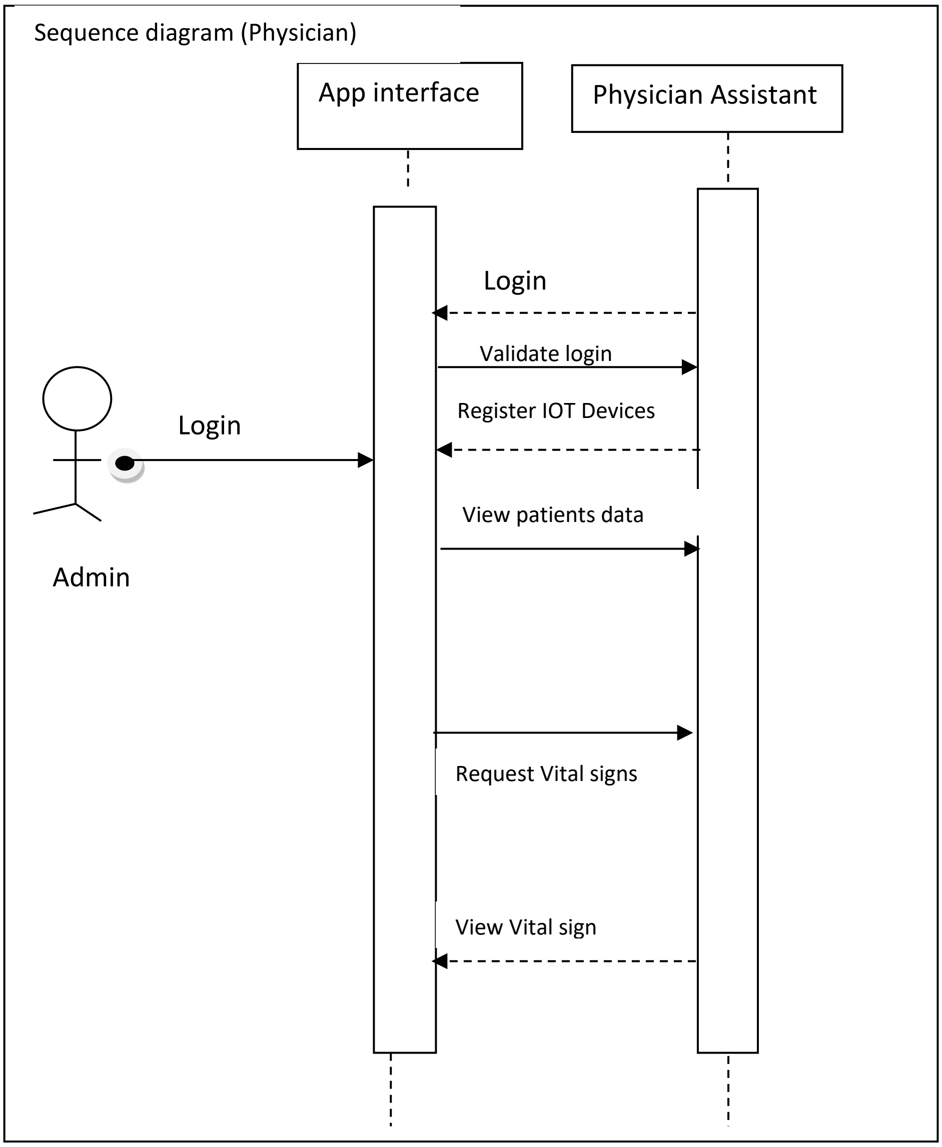

Figure 6: Sequence Diagram (Physician)

Table 2: SYSTEM ALGORITHM

INPUT	Sample 50 IoT Sensor Records Test Dataset
OUTPUT	Smart Based IoT Optimization Framework using Federated Learning (FL) Approach for Healthcare

VII. RESULTS

EXPERIMENT USING THE ALGORITHMS

The first process was
1. Initialize global model at the FL server.
2. Register IoT devices and collect device metrics (ip-address).
3. Optimization Engine selects best devices for the next FL round.
4. Server distributes the global model to selected devices.
5. Devices collect local patient data (sensor readings).
6. Local preprocessing (cleaning, feature extraction, normalization).
7. Local model training using device's private dataset.
8. Devices compress + secure model updates (e.g., DP noise).

9. Transmit model updates to server.
10. Server aggregates updates (FedAvg).
11. Global model updated and redistributed.
12. Dashboard updates analytics after each round.
13. Repeat next optimization + FL round.

PERFORMANCE EVALUATION EXPERIMENT

To evaluate the predictive performance of the Federated Learning (FL) global model in detecting abnormal healthcare conditions (e.g., abnormal heart rate, temperature anomalies), several statistical evaluation metrics were computed. These include:

1. Confusion Matrix
2. Precision, Recall, F1-Score
3. Sensitivity and Specificity
4. Interpretation of results

1. Confusion Matrix

A binary classifier was used, where:

1 = Abnormal event detected

0 = Normal reading

The confusion matrix for the final global model is shown below using 1000 records:

Table 3: Confusion Matrix

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

Interpretation of Confusion Matrix

True Positives (TP) = 105

True Negatives (TN) = 820

False Positives (FP) = 45

False Negatives (FN) = 30

We will compute the following:

1. Precision
2. Recall (Sensitivity)
3. Accuracy
4. F1-Score
5. False Positive Rate (FPR)
6. False Negative Rate (FNR)
7. Negative Predictive Value (NPV)

Precision (P): Precision of all predicted positives, how many are correct?

$$\text{Precision} = \frac{TP}{TP+FP} \qquad 1.0$$

$$\text{Precision} = \frac{105}{105+45}$$ Precision = 0.70 ≈ 0.70 = 70%

Recall (R) (Sensitivity): Recall of all actual positives, how many was detect?

$$\text{Recall(Sensitivity)} = \frac{TP}{TP+FN} \qquad 2.0$$

$$\text{Recall} = \frac{105}{105+30}$$ Recall = 0.778 ≈ 0. 78 = 78%

Accuracy: Measures how well the FL global model predicts target outcomes

$$\text{Accuracy}\frac{TP+TN}{TP+FN+FP+FN} \qquad 3.0$$

$$\text{Accuracy} = \frac{105+820}{105+820+45+30}$$ Accuracy = 0.925 ≈ 0. 93= 93%

F1 Score: Harmonic mean of Precision and Recall.

$$\text{F1} - \text{Score Formula} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision + Recall}} \qquad 4.0$$

$$\text{F1 score} = \frac{2 \text{ x } 0.70\times0.78}{0.70+ 0.78}$$ F1 score = 0.738 ≈ 0.74 = 74%

False Positive Rate (FPR):

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN} \quad 5.0$$

$$\text{False Positive Rate (FPR)} = \frac{45}{45+820} = 0.052 \approx 0.05 = 5\%$$

False Negative Rate (FNR):

$$\text{False Negative Rate (FNR)} = \frac{FN}{FN+TP} \quad 6.0$$

$$\text{False Negative Rate (FNR)} = \frac{30}{30+105} = 0.222 \approx 0.22 = 22\%$$

Negative Predictive Value (NPV):

$$\text{Negative Predictive Value (NPV)} = \frac{TN}{TN+FN} \quad 7.0$$

$$\text{Negative Predictive Value (NPV)} = \frac{820}{820+30} = 0.964 \approx 0.96 = 96\%$$

This means 96% of the time, when the model predicts *normal*, the patient is truly normal.

Table 4: Final Summary (All Metrics)

Metric	Value (%)
Precision	70%
Recall (Sensitivity)	78%
Accuracy	93%
F1-Score	74%
FPR	5%
FNR	22%
NPV	96%

VIII. OUTPUT OF THE EXPERIMENT

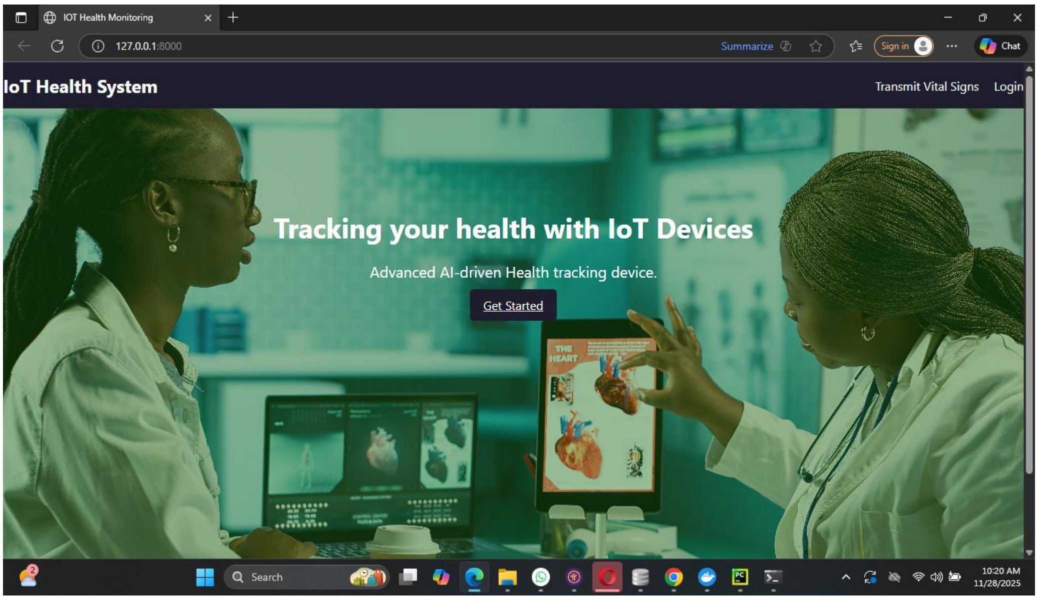

Figure 7: Home Page Interface

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The landing page of the IoT based health monitoring Device. Before any user could monitor any patients health status, an account and access must be guaranteed. The Admin could also access the device to update or monitor any health cases through the interface shown in figure 8 below.

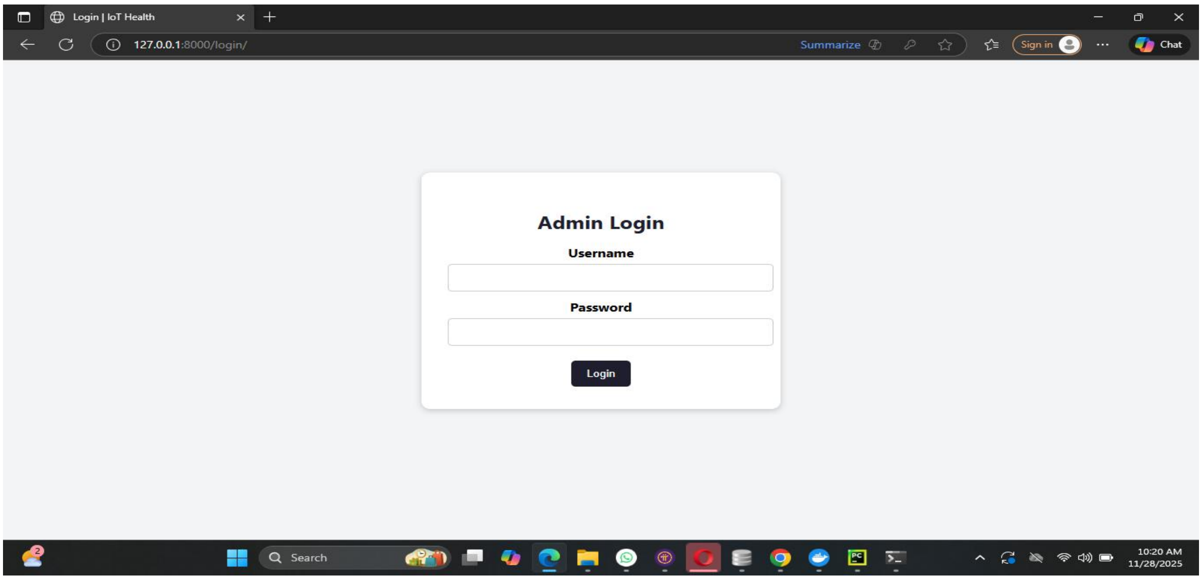

Figure 8: Admin Login Page Interface

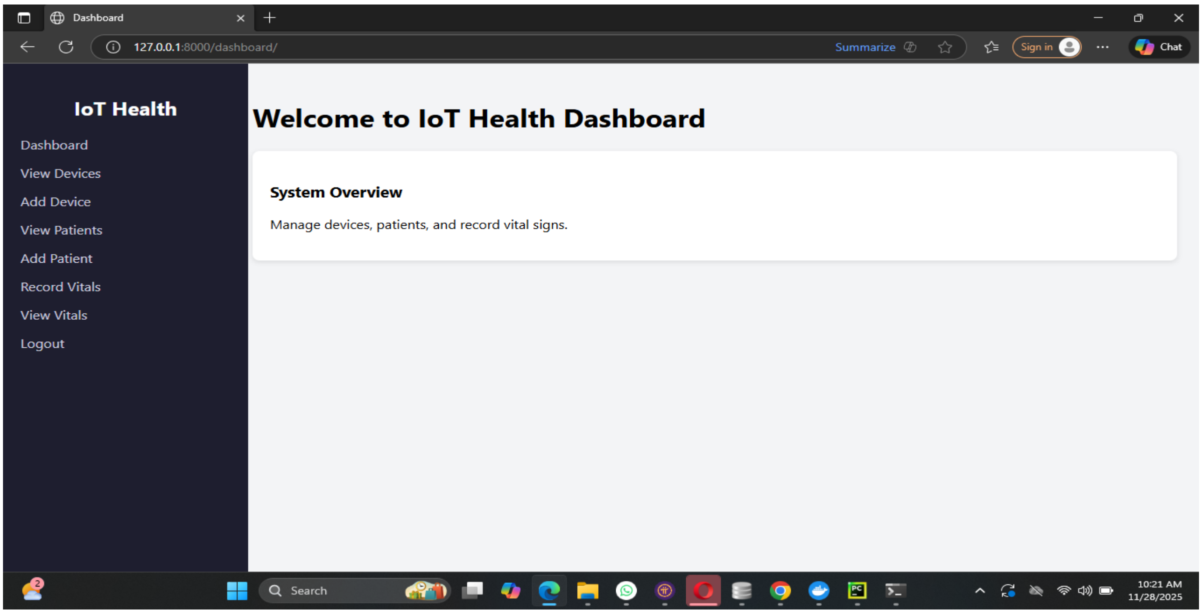

Figure 9: Admin Dashboard Interface

The Dashboard of the System provides all the required privileges any user has over a particular platform.

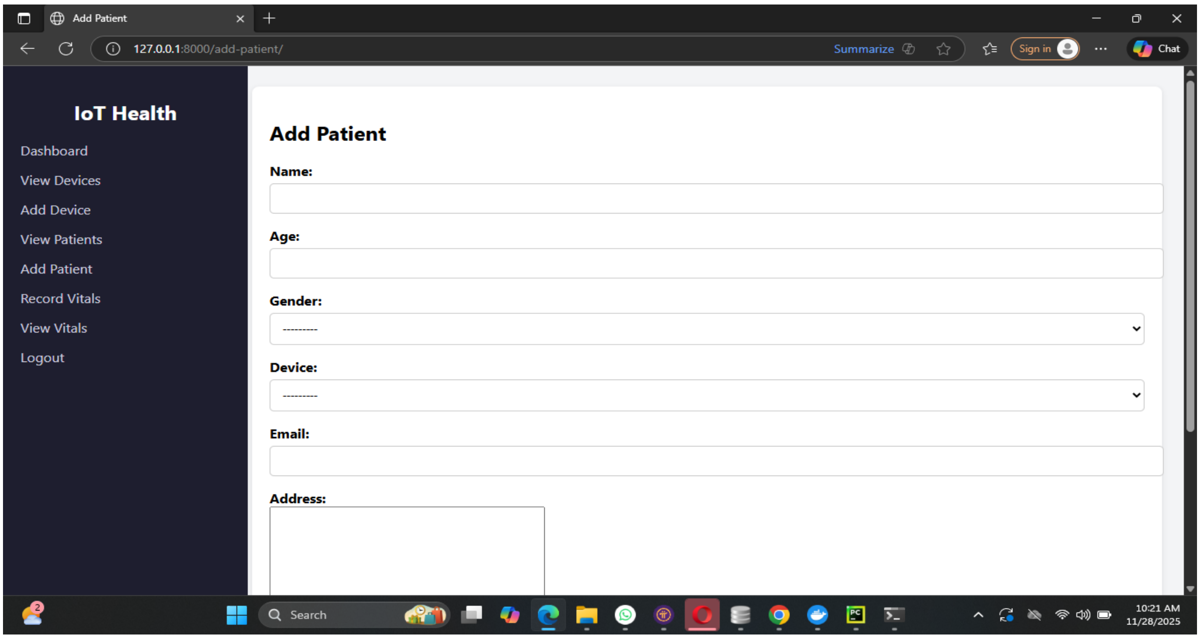

Figure 10: Patient Registration Form

This interface helps users to add patients into the System by collecting relevant information about the patients.

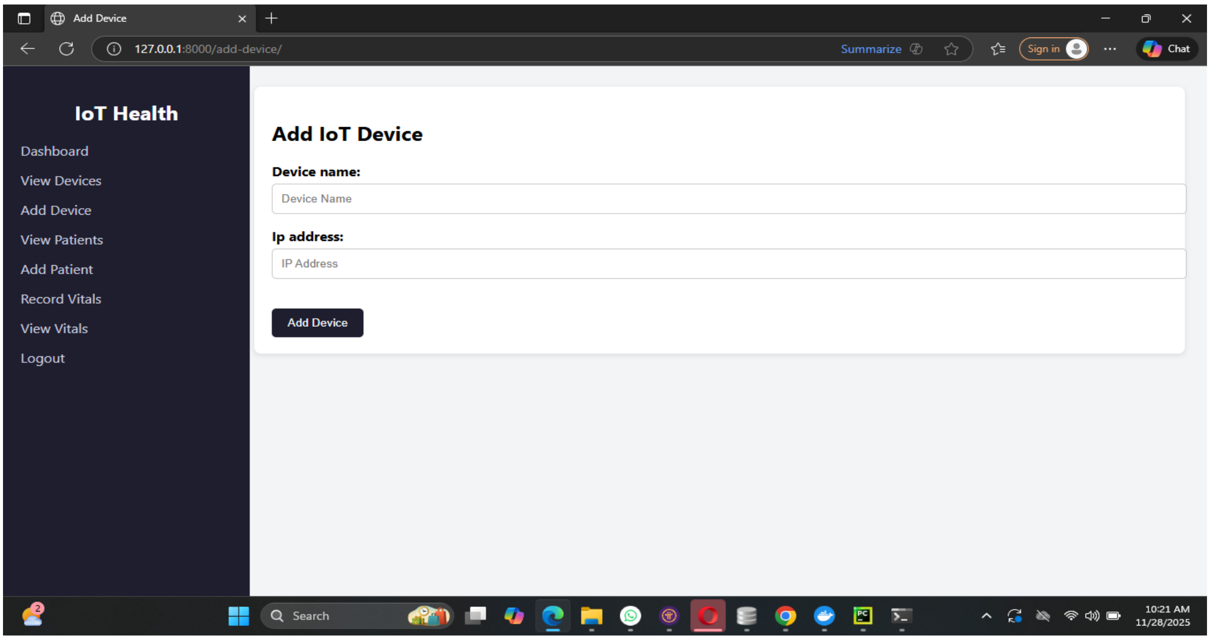

Figure 11: IoT Device Registration Form

The IoT device interface helps to add new IoT technological tools to the proposed System to enable reliable performance and accuracy towards predicting and monitoring patients health status.

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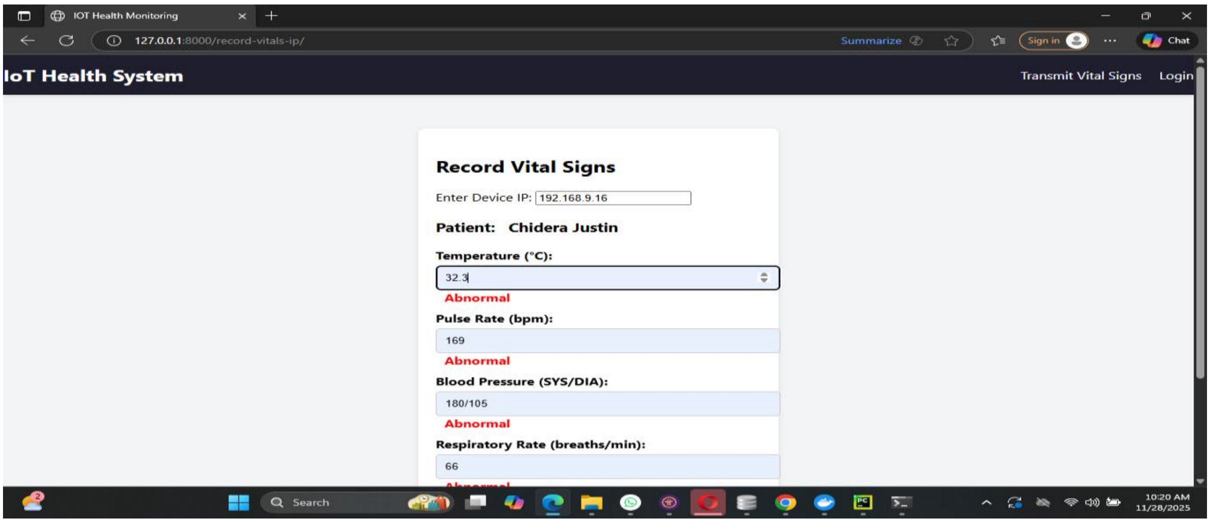

Figure 12: IoT Device Data Capturing and Training

This interface shown in figure 12 above provides an easier means of collecting health and related vitals from patients by the IoT device and at the same time process the collected information which in turn suggest and displays health status of the patients. The display of the patients records are also shown in figure 13 below. The records contains the IoT device that performed the action, the date and time of the action, patients names, blood pressure and pulse rate of the patients as well as the patients temperature.

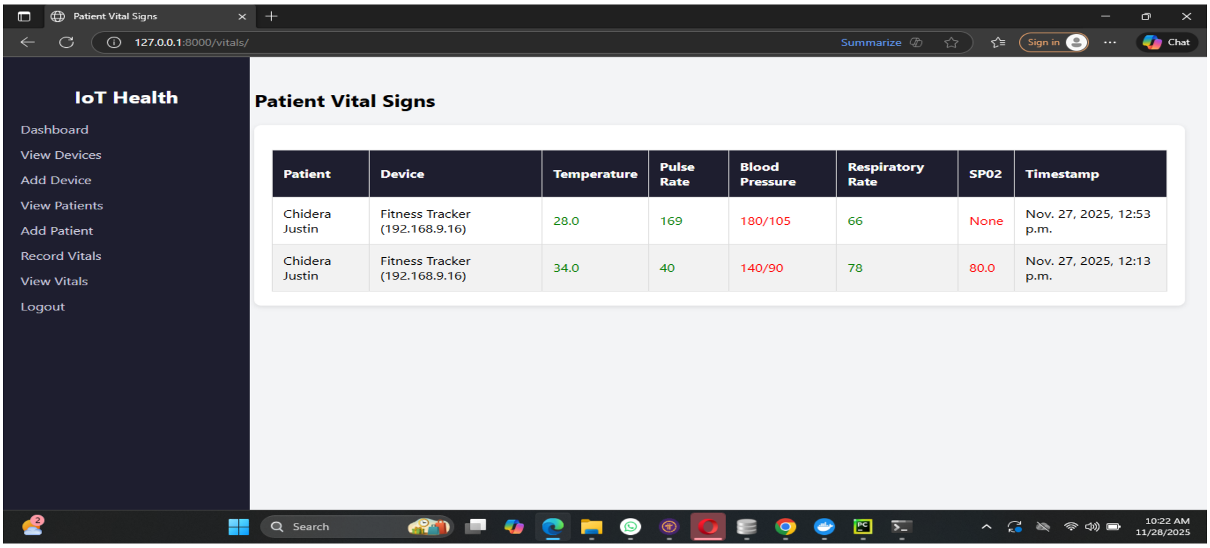

Figure. 13: Patient Vital Signs Transmitted

IX. CONCLUSION

This research successfully developed and evaluated an intelligent IoT device optimization system powered by Machine Learning. The system resolves critical issues in healthcare data management by allowing private, decentralized model training on IoT devices while maintaining high predictive accuracy and optimal device performance. The results demonstrate that Machine Learning is not only feasible but also highly effective in healthcare scenarios where privacy, security, and real-time responsiveness are essential. The solution ensures robust anomaly detection, reduces communication costs, and preserves device energy making it ideal for continuous patient monitoring.

In conclusion, the proposed system stands as a practical and scalable framework for future smart healthcare deployments, laying the groundwork for next-generation privacy-preserving medical analytics.

X. RECOMMENDATIONS

Based on the findings of this study, the following recommendations are made:

1. Deploy FL-enabled IoT systems in healthcare centers: Hospitals should adopt FL-based monitoring to enhance patient privacy and reduce reliance on centralized databases.
2. Increase hardware resources on edge devices: IoT nodes with stronger computing power will improve local training performance and reduce latency.
3. Expand dataset variety: Incorporating more diverse sensor datasets will further improve the generalization and accuracy of the system.

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