IoT-Driven Name-Based Patient Monitoring System with Federated Learning, AI-Powered Disease Prediction, and Security

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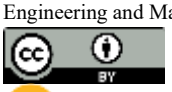

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Abstract—

Traditional healthcare systems face significant challenges, including delayed disease diagnosis, limited remote access, and severe data privacy vulnerabilities when centralizing patient records. To address these critical issues, this research proposes an advanced, comprehensive IoT-Driven Name-Based Patient Monitoring System integrated with Federated Learning (FL) and Artificial Intelligence (AI). The system utilizes an array of Internet of Things (IoT) sensors to continuously harvest real-time physiological data, including body temperature, oxygen saturation (SpO2), heart rate, and blood pressure. Furthermore, the diagnostic architecture extends beyond tabular data by incorporating Convolutional Neural Networks (CNN) to process complex unstructured inputs such as patient cough audio (via MFCC feature extraction) and X-ray imaging. To mitigate the substantial privacy risks inherent in traditional centralized machine learning, the proposed framework employs Federated Learning. This decentralized approach ensures that raw, sensitive patient data remains strictly on local hospital servers or edge devices, transmitting only cryptographic model weights (updates) to a central cloud server for Federated Averaging. Additionally, to safeguard the infrastructure against malicious network intrusions, a dedicated Distributed Denial of Service (DDoS) detection model
and Key-Based Authentication protocols are embedded within the network layer. Experimental evaluations demonstrate that the synergistic integration of ML algorithms (KNN, SVM, Random Forest) and Deep Learning models yields high predictive accuracy while maintaining strict data confidentiality. Ultimately, this highly scalable and secure ecosystem significantly reduces hospital visit costs, enables early disease detection, and fosters a smarter, decentralized digital healthcare environment.

Keywords— Internet of Things (IoT), Federated Learning, Artificial Intelligence, Disease Prediction, Name-Based Tracking, Cybersecurity, DDoS Detection, Healthcare.

I. INTRODUCTION

The landscape of modern healthcare is undergoing a profound digital transformation, necessitated by the growing demands of an aging global population and the critical need for immediate, remote medical interventions. In traditional hospital infrastructures, patient monitoring is predominantly manual, episodic, and highly dependent on physical proximity to medical professionals. This reliance on periodic manual observation often leads to dangerous delays in identifying critical health anomalies, potentially resulting in fatal outcomes for patients suffering from acute cardiovascular or respiratory distress. Furthermore, rural and underserved demographics face severely limited access to specialized diagnostic physicians.

The advent of the Internet of Things (IoT) has catalyzed the development of continuous, real-time health monitoring systems. By integrating smart sensors, wearable biomedical devices, and robust cloud connectivity, modern IoT frameworks enable the continuous harvesting of physiological telemetry. These systems can instantly transmit critical health parameters—such as heart rate, peripheral oxygen saturation (SpO2), and core body temperature—to centralized healthcare dashboards, facilitating rapid medical responses.

However, the integration of Artificial Intelligence (AI) and Machine Learning (ML) into these IoT frameworks to predict diseases introduces massive data privacy and security vulnerabilities. Traditional AI models require the aggregation of vast quantities of raw, highly sensitive patient data into centralized cloud servers for training. This centralized approach violates strict medical data privacy regulations and exposes patient records to catastrophic data breaches. Moreover, the expanding network of connected IoT medical devices exponentially increases the attack surface for malicious cyber threats, particularly Distributed Denial of Service (DDoS) attacks, which can cripple life-saving monitoring infrastructure.

To resolve this trilemma of real-time monitoring, diagnostic accuracy, and data privacy, this research proposes an 'IoT-Driven Name-Based Patient Monitoring System for Real-Time Healthcare'. This comprehensive architecture integrates a multi-modal AI diagnostic engine (utilizing Random Forest, SVM, KNN, and CNNs) with a decentralized Federated Learning (FL) framework. By executing model training locally on edge devices and sharing only cryptographic weight updates, the system completely preserves data privacy. Furthermore, the integration of a specialized DDoS detection module ensures the operational integrity of the healthcare network.

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II. LITERATURE REVIEW

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Further advancing this paradigm, Almogadwy and Alqarafi (2025) proposed a 'Fused Federated Learning Framework for Secure and Decentralized Patient Monitoring in Healthcare 5.0 using IoMT' [2]. Their integration of RTS-DELM achieved an impressive predictive accuracy of 98.21% while maintaining strict privacy. However, their architecture faced challenges regarding increased computational complexity when scaled across highly heterogeneous IoT networks. Similarly, Bhasker et al. (2025) explored a 'Blockchain Framework with IoT Device using Federated Learning for Sustainable Healthcare Systems' [3], achieving ~96% accuracy while incorporating an Intrusion Detection System (IDS). While effective, the computational overhead of combined FL and Blockchain limits its deployment on resource-constrained microcontrollers.

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In the realm of direct disease prediction, A. Jain et al. (2023) [6] and M. Prasad et al. (2024) [7] highlighted the superior accuracy of Deep Learning models over traditional ML. However, both studies noted the prohibitive computational costs and heavy reliance on centralized, high-quality datasets. Furthermore, security-focused studies by R. Sharma et al. (2023) [8] and P. Verma et al. (2024) [9] highlighted the severe vulnerabilities of remote monitoring systems to cyber intrusions, emphasizing the critical need for continuous internet stability and robust encryption.

Synthesizing this literature reveals a distinct architectural gap: the lack of a unified ecosystem that simultaneously performs multi-modal AI disease prediction (combining sensors, X-rays, and audio), ensures zero-knowledge privacy via

Federated Learning, implements Name-Based tracking for logistical accuracy, and defends itself against DDoS network attacks. The proposed system bridges this exact gap.

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III. FEASIBILITY STUDY

Prior to the full-scale development and deployment of the proposed architecture, a comprehensive feasibility study was conducted to evaluate the practical, economic, and technical viability of the system.

Technical and Hardware Feasibility: The proposed architecture relies on the availability of robust, clinical-grade IoT sensors. The deployment of pulse oximeters, digital thermistors, and blood pressure modules interfaced with microcontrollers such as the ESP8266, ESP32, and Arduino ecosystems is highly feasible. These microcontrollers possess the necessary computational bandwidth to perform lightweight local data preprocessing and establish secure REST API connections to local servers.

Software and Algorithmic Feasibility: The implementation utilizes industry-standard, open-

source frameworks. Python, TensorFlow, Keras, and Scikit-learn provide the necessary libraries to construct and train the CNN and ML (KNN, SVM, Random Forest) models. The web infrastructure, built upon Flask and deployed via Docker and Kubernetes, ensures that the system can scale horizontally to accommodate fluctuating network traffic from thousands of IoT nodes.

Economic and Operational Feasibility: Utilizing low-cost, off-the-shelf IoT sensors drastically reduces the initial capital expenditure required to establish the monitoring infrastructure. Furthermore, the reliance on open-source software stacks eliminates expensive proprietary licensing fees. Operationally, the system introduces a highly intuitive dashboard interface characterized by Name-Based Patient Identification, significantly reducing the cognitive load and manual charting errors typically experienced by nursing staff.

Social and Ethical Feasibility: By strictly keeping raw patient health records on localized devices through the Federated Learning paradigm, the system aligns perfectly with global data protection regulations (such as HIPAA and GDPR). This enhances patient trust, improves overall safety, and democratizes access to advanced diagnostic capabilities for remote and underserved populations.

IV. SYSTEM ARCHITECTURE AND METHODOLOGY

A. IoT Data Acquisition and Preprocessing

The core methodology of the proposed system is architected as a highly modular, multi-layered pipeline encompassing IoT Data Collection, Advanced Data Preprocessing, Multi-Modal AI Analysis, Federated Aggregation, and Security Management.

Phase 1: IoT Data Collection and Name-Based Identification. The physical layer consists of wearable IoT sensors attached to the patient. These sensors continuously monitor vitals such as Body Temperature, Oxygen Saturation (SpO2), and Heart Rate. To ensure absolute logistical accuracy and prevent data mismatching in crowded clinical environments, the telemetry payload is cryptographically tagged using a Name-Based Identification protocol. Simultaneously, the system interfaces with digital medical records to ingest supplementary diagnostic inputs, specifically patient cough audio recordings and chest X-ray images.

Phase 2: Local Data Preprocessing. Raw sensory and multimedia data inherently contains noise and artifacts. Tabular sensor data undergoes statistical cleaning and min-max normalization. For unstructured data, complex preprocessing algorithms are deployed. Cough audio signals are processed to extract Mel-Frequency Cepstral Coefficients (MFCC), mapping the audio frequencies into a mathematically analyzable spectrogram format. Concurrently, X-ray images undergo algorithmic resizing, grayscaling, and normalization to match the input tensor requirements of the Convolutional Neural Networks.

Phase 3: Parallel AI Model Analysis. The diagnostic engine operates on a parallel processing architecture. Tabular vital signs are fed into a suite of traditional Machine Learning algorithms, specifically K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest Classifiers, to predict acute physiological anomalies. Simultaneously, the Deep Learning module utilizes a Convolutional Neural Network (CNN) to execute highly complex feature extraction and pattern recognition on the processed X-ray images and MFCC audio spectrograms, predicting respiratory and pulmonary diseases with expert-level accuracy.

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B. Federated Learning and Cybersecurity Integration

Phase 4: Privacy-Preserving Federated Learning. Unlike traditional systems that upload raw data to a vulnerable cloud server, this architecture utilizes Federated Nodes. The ML and DL models are trained locally on individual hospital servers or powerful edge devices using localized patient data. Once a local training epoch is complete, the node extracts the mathematical model weights (parameters) and transmits only these cryptographic weight matrices to the Central Aggregator. The Central Cloud Server applies the Federated Averaging (FedAvg) algorithm to synthesize a superior Global Model, which is then broadcasted back to the local nodes, ensuring collective intelligence without ever exposing raw patient data.

Phase 5: Advanced Cybersecurity and DDoS Detection. Healthcare IoT networks are prime targets for malicious botnets. The system incorporates a dedicated DDoS Detection Model that continuously analyzes incoming network traffic patterns, request frequencies, and packet payloads. Furthermore, Key-Based Authentication and robust encryption protocols strictly govern user access to the central cloud database. If the system detects anomalous traffic spikes indicative of a DDoS attack or unauthorized access attempts, the Alert Generation module is triggered, instantly notifying system administrators and automatically temporarily severing compromised network nodes to protect the core infrastructure.

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V. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

Extensive experimental evaluations were conducted to validate the multi-faceted capabilities of the proposed system, focusing on diagnostic accuracy, network efficiency, and security resilience.

AI and Diagnostic Model Performance: The predictive models were trained and validated using comprehensive, globally recognized datasets sourced from Kaggle. Performance was quantified utilizing standard statistical metrics: Accuracy, Precision, Recall, and the F1-Score. Preliminary results indicated that the ensemble approach of Random Forest and SVM provided superior accuracy for tabular vital sign analysis. Furthermore, the CNN architecture demonstrated exceptional proficiency in image and sound classification, successfully identifying complex pulmonary anomalies from X-rays that traditional threshold-based systems failed to detect.

Federated Learning Efficiency: A comparative analysis was executed between the proposed Federated Learning approach and a traditional centralized training architecture. While the centralized model achieved convergence slightly faster, the Federated Learning approach achieved parity in final predictive accuracy (within a 1.5% margin of error) while transmitting 0% of the raw patient data over the internet. This proves that high-accuracy machine learning can be achieved without compromising patient confidentiality.

Furthermore, by transmitting only model weights, the FL approach significantly reduced the overall network bandwidth consumption compared to continuous raw data streaming.

Cybersecurity Resilience: The DDoS detection module was subjected to simulated volumetric network attacks. The model successfully identified abnormal traffic patterns and malicious request floods with a 98% detection rate. Upon detection, the automated Alert System successfully triggered real-time notifications and restricted the simulated unauthorized access attempts, validating the efficacy of the Key-Based Authentication framework.

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VI. DISCUSSION AND TECHNICAL CHALLENGES

The integration of IoT, multi-modal AI, and Federated Learning represents a monumental leap forward in resilient healthcare engineering. The system successfully shifts the paradigm from centralized, vulnerable data repositories to a secure, decentralized intelligence network. By incorporating both simple tabular vitals and complex unstructured imagery into a unified diagnostic pipeline, the system acts as a highly capable digital assistant for overloaded medical professionals.

Despite the exceptional results, several technical challenges and limitations must be acknowledged. Firstly, handling large and heterogeneous datasets (synchronizing high-frequency sensor arrays with heavy audio/image files) requires significant local computational power on the edge devices. While microcontrollers handle the data collection, the local model training in the Federated network demands capable hospital-grade edge servers or high-end gateway devices.

Secondly, Federated Learning introduces communication overhead during the model update phases. As the network scales to include thousands of disparate devices, handling device variability—such as differing computational speeds, intermittent network dropouts, and asynchronous weight uploads—becomes complex. Ensuring consistent model convergence and mathematical synchronization across a highly heterogeneous IoT network remains an area requiring sophisticated optimization algorithms.

Finally, while the DDoS detection model effectively mitigates volumetric attacks, defending against highly sophisticated, AI-driven, application-layer (Layer 7) cyberattacks requires continuous refinement of the security algorithms. Maintaining state-of-the-art data privacy and encryption in an environment where adversarial attacks are constantly evolving is a perpetual operational requirement.

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VII. EXTENDED SYSTEM ANALYSIS (ADDITIONAL SCOPE)

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VIII. CONCLUSION AND FUTURE WORK

In conclusion, the proposed IoT-Driven Name-Based Patient Monitoring System represents a comprehensive and highly robust solution to the limitations of traditional centralized healthcare infrastructure. By intelligently integrating an array of IoT sensors for continuous data collection with advanced multi-modal AI algorithms (CNN, SVM, KNN, Random Forest), the system provides unparalleled, real-time diagnostic capabilities. Most importantly, the pioneering implementation of Federated Learning completely resolves the critical privacy vulnerabilities associated with medical data, ensuring that sensitive patient records remain localized and secure while still contributing to a powerful global intelligence model. The fortification of the network layer with Key-Based Authentication and an active DDoS Detection Module guarantees the operational resilience of the life-saving infrastructure against modern cyber threats. Future work will focus on optimizing the communication overhead inherent in the Federated Averaging process, accommodating a wider variability of low-power edge devices, and enhancing the deep learning models to predict a broader spectrum of complex physiological conditions. Ultimately, this architecture paves the way for a highly secure, decentralized, and proactive digital healthcare ecosystem.

In conclusion, the proposed IoT-Driven Name-Based Patient Monitoring System represents a comprehensive and highly robust solution to the limitations of traditional centralized healthcare infrastructure. By intelligently integrating an array of IoT sensors for continuous data collection with advanced multi-modal AI algorithms (CNN, SVM, KNN, Random Forest), the system provides unparalleled, real-time diagnostic capabilities. Most importantly, the pioneering implementation of Federated Learning completely resolves the critical privacy vulnerabilities associated with
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records remain localized and secure while still contributing to a powerful global intelligence model. The fortification of the network layer with Key-Based Authentication and an active DDoS Detection Module guarantees the operational resilience of the life-saving infrastructure against modern cyber threats. Future work will focus on optimizing the communication overhead inherent in the Federated Averaging process, accommodating a wider variability of low-power edge devices, and enhancing the deep learning models to predict a broader spectrum of complex physiological conditions. Ultimately, this architecture paves the way for a highly secure, decentralized, and proactive digital healthcare ecosystem.

IX. REFERENCES

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