Smart Healthcare System Using Internet of Things (IOT): A Comprehensive Study, Framework and Performance Evaluation

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ABSTRACT

The Internet of Things (IoT) is transforming conventional healthcare delivery into a proactive, connected and data-driven ecosystem popularly known as Smart Healthcare. By embedding sensors, wearable devices and communication modules into everyday medical objects, IoT enables continuous monitoring of vital physiological parameters such as heart rate, blood pressure, oxygen saturation (SpO2), body temperature and glucose level, without requiring the patient to be physically present at a clinic. This paper presents a comprehensive review and an original three-layer architecture (Perception, Network and Application) for an IoT-based smart healthcare system that integrates edge pre-processing with cloud-based analytics to reduce latency and improve reliability. We survey a set of recent works published between 2018 and 2024, classify them by sensing modality, communication protocol and machine-learning technique, and identify open research gaps such as interoperability, energy efficiency and security. A prototype pipeline combining an ESP32 microcontroller, MAX30100 pulse-oximeter sensor, MQTT protocol and a Random Forest classifier is evaluated on a benchmark vital-sign dataset, achieving 96.7% classification accuracy and an average end-to-end latency of 118 ms, outperforming five baseline architectures compared in this study. The results confirm that a hybrid edge-cloud design offers the best trade-off between accuracy, latency and energy consumption for real-time patient monitoring. Future directions including 6G-enabled healthcare, federated learning for privacy preservation, and blockchain-based health record management are also discussed.

Keywords: Internet of Things (IoT), Smart Healthcare, Remote Patient Monitoring, Wearable Sensors, Machine Learning, Edge Computing, MQTT, Wireless Body Area Network (WBAN)

INTRODUCTION

Healthcare systems worldwide are under increasing pressure due to ageing populations, the rising prevalence of chronic diseases and a shortage of clinical staff. Traditional healthcare delivery is largely reactive, a patient visits a hospital only after symptoms appear, by which time a condition may have progressed significantly. The Internet of Things (IoT) offers a paradigm shift from this reactive model to a continuous, proactive and personalised model of care.

An IoT-based smart healthcare system typically consists of wearable or implantable sensors that continuously capture physiological signals, a communication layer that transmits this data to gateways or cloud servers, and an intelligent analytics layer that interprets the data to detect anomalies, predict risk, and alert caregivers in real time. Such systems have been successfully applied to remote patient monitoring, elderly care, chronic disease management (diabetes, cardiac conditions), and emergency response.

Despite significant progress, existing smart healthcare solutions face persistent challenges: high latency when all processing is offloaded to the cloud, limited battery life of wearable sensors, lack of interoperability between heterogeneous devices and protocols, and concerns regarding data privacy and security of sensitive medical information. This paper addresses these gaps by proposing a hybrid edge-cloud architecture and by benchmarking it against prior work.

Background: why IoT for healthcare

The convergence of low-cost microcontrollers, miniaturised biomedical sensors and ubiquitous wireless connectivity has made continuous, unobtrusive health monitoring technically and economically feasible for the first time. A Wireless Body Area Network (WBAN), a network of small, low-power sensor nodes placed on or near the human body, forms

the foundational building block of most smart healthcare deployments. Unlike a single annual check-up, a WBAN generates a continuous physiological time-series that can reveal early warning signs, such as gradually rising blood pressure or irregular heart rhythm, long before they become clinically apparent through conventional means.

At the same time, healthcare-generated IoT data is uniquely sensitive: a compromised fitness tracker exposes inconvenience, but a compromised cardiac monitor can expose a life-threatening condition or, worse, be tampered with. This dual requirement of real-time responsiveness and stringent data protection makes smart healthcare one of the most demanding application domains within the broader IoT ecosystem, and is the central tension this paper investigates.

Motivation and contribution

- A structured literature review of recent IoT-healthcare studies published between 2018 and 2024.
- A three-layer reference architecture combining edge pre-processing with cloud analytics.
- A working prototype using low-cost, off-the-shelf hardware (ESP32 and MAX30100).
- A comparative performance evaluation against five baseline architectures using accuracy and latency as metrics.

Paper organisation

The Literature Review section reviews related literature and derives research gaps. The Research Methodology section describes the proposed system architecture and experimental setup. The Results section presents comparative analysis using tables and graphs. The Discussion section interprets the findings, the Conclusion summarises the study, and the Future Scope section outlines directions for continued research, followed by references organised year-wise.

LITERATURE REVIEW

A structured review of the literature published between 2018 and 2024 was conducted using IEEE Xplore, ScienceDirect and Springer databases with the keywords "IoT healthcare", "remote patient monitoring" and "smart health sensors". Table 1 summarises representative works, the sensing modality used, the communication protocol, and the reported accuracy or limitation.

Author (Year)	Focus Area	Technology Used	Key Result / Limitation
Islam et al. (2018)	Survey of IoT-health architectures	RFID, ZigBee, 6LoWPAN	Comprehensive taxonomy; no real deployment
Kumar et al. (2019)	ECG monitoring	Wearable ECG + Wi-Fi	86.2% arrhythmia detection accuracy; high power use
Islam et al. (2020)	Fall detection for elderly	Accelerometer + Cloud ML	89.5% accuracy; high cloud latency (~420 ms)
Rani et al. (2021)	Diabetes risk prediction	Glucose sensor + SVM	91.0% accuracy; limited dataset size
Verma et al. (2022)	Fog-based vitals monitoring	Fog computing + MQTT	92.8% accuracy; latency ~265 ms
Alam et al. (2023)	Edge-AI health monitoring	Edge device + CNN	94.1% accuracy; energy overhead on edge node
Chen et al. (2023)	Security in IoT-health	Blockchain + AES-256	Improved data integrity; added transaction delay
Patel et al. (2024)	Federated learning for health data	Federated ML across hospitals	Preserves privacy; needs synchronisation overhead

Table 1. Summary of Related Work (2018–2024)

The review reveals a clear upward trend in classification accuracy over time as machine-learning techniques matured, but also shows that cloud-centric designs consistently suffer from higher latency, while edge-only designs trade accuracy for speed. This observation directly motivates the hybrid architecture proposed in the Research Methodology section. Furthermore, very few of the reviewed works explicitly address security and privacy, indicating this remains an under-explored area.

Communication protocols and ML techniques reviewed

Bluetooth Low Energy and ZigBee are favoured for short-range, ultra-low-power body sensors, while Wi-Fi and 4G/5G modules reach the cloud from the gateway. At the application layer, MQTT has emerged as the dominant choice over HTTP/REST because its publish-subscribe model and small header size reduce bandwidth and battery consumption; CoAP is a comparable lightweight alternative. On the modelling side, classical machine-learning models such as Logistic Regression, SVM and Random Forest dominate earlier works (2018-2021) owing to their low computational footprint, while deep-learning approaches such as CNNs and LSTMs appear more frequently from 2021 onward, driven by their ability to model temporal patterns in ECG and PPG waveforms at a higher computational cost.

Research gaps identified

- Latency-accuracy trade-off: cloud-centric designs achieve high accuracy but unacceptable latency for emergencies, while edge-only designs are fast but less accurate.
- Interoperability: heterogeneous sensor vendors and protocols hinder plug-and-play deployment across care settings.
- Energy efficiency: continuous sensing and wireless transmission remain the dominant sources of battery drain in wearable nodes.
- Security and privacy: relatively few studies implement end-to-end encryption or formal privacy-preserving mechanisms for medical data in transit and at rest.
- Limited real-world validation: most studies, including this one, rely on benchmark or simulated datasets rather than large-scale clinical deployments.

RESEARCH METHODOLOGY

This study follows an applied, design-science research approach: a candidate architecture is proposed based on gaps identified in the literature, implemented as a working prototype, and then empirically evaluated against established baselines using controlled experiments. This methodology was chosen over a purely simulation-based study because hardware-in-the-loop testing captures real network jitter, sensor noise and processing delay that idealised simulations tend to underestimate.

Proposed system architecture

The proposed system follows a three-layer architecture, summarised in Table 2:

Layer	Components	Primary Function
Perception Layer	MAX30100 (HR/SpO2), DHT11 (Temp), MPU6050 (motion), ESP32 microcontroller	Continuous sensing and local range validation
Network Layer	Wi-Fi, MQTT broker (TLS), edge gateway	Lightweight, low-latency data transport and pre-screening
Application Layer	Cloud server, Random Forest classifier, mobile dashboard	Final classification, alerting, storage and visualisation

Table 2. Proposed Three-Layer System Architecture

Dataset and pre-processing

The classifier was trained and validated on a benchmark vital-signs dataset (heart rate, SpO2, temperature, systolic/diastolic blood pressure) comprising 10,000 labelled instances categorised as Normal, At-Risk, or Critical. Missing values were imputed using mean substitution, and features were normalised using min-max scaling before an 80:20 train-test split.

Class balance was checked prior to training: the dataset contained approximately 70% Normal, 22% At-Risk and 8% Critical instances, reflecting the expected distribution of a general monitoring population. To prevent the classifier from being biased toward the majority class, class weights were adjusted inversely proportional to class frequency during Random Forest training, which improved recall on the minority Critical class by approximately 4 percentage points relative to an unweighted baseline.

Machine learning model

A Random Forest classifier (100 estimators, max depth 12) was selected after comparing it against Logistic Regression, Support Vector Machine (SVM) and a shallow Artificial Neural Network (ANN) on the same split, as it provided the best balance of accuracy and inference speed suitable for near-real-time alerts.

Random Forest was preferred over deep-learning alternatives for this deployment because it trains and infers quickly on modest cloud instances without a GPU, is naturally robust to the mixed-scale numerical features present in vital-sign data, and produces feature-importance scores that give clinicians an interpretable view of which readings drove a given alert, an important consideration for clinical trust and regulatory acceptance, unlike typical black-box deep networks.

System workflow

The end-to-end operation of the proposed system follows the steps below:

- Step 1: The sensor node samples heart rate, SpO2, temperature and motion at a fixed interval of five seconds.
- Step 2: The ESP32 performs local range-checking; obviously invalid readings caused by sensor noise are discarded.
- Step 3: Valid readings are published as a JSON payload to the MQTT broker over Wi-Fi.
- Step 4: The edge gateway subscribes to the topic and applies a lightweight rule-based pre-screen, for example flagging heart rate above 130 or SpO2 below 90 as a possible risk.
- Step 5: Normal readings are logged for trend analysis only, while flagged readings are forwarded immediately to the cloud.
- Step 6: The cloud-hosted Random Forest classifier assigns a final label of Normal, At-Risk, or Critical.
- Step 7: Critical or At-Risk labels trigger a push notification to the caregiver's mobile dashboard with the patient ID, timestamp and vitals snapshot.

Security and privacy considerations

Given the sensitivity of medical data, the prototype applies TLS-encrypted MQTT between the gateway and broker, and AES-128 encryption for data at rest on the cloud database. Device authentication uses per-node API keys, and patient identifiers are pseudonymised before storage to reduce re-identification risk. These measures address, in part, the security gap identified in the Literature Review section, though a full formal security evaluation is left as future work.

Evaluation metrics

- Classification accuracy, precision, recall and F1-score.
- End-to-end latency: time from sensor reading to alert delivery.
- Energy consumption of the sensor node under continuous operation.
- Comparative benchmarking against cloud-only, fog-based and edge-only baseline architectures.

RESULTS

Figure 1 compares the classification accuracy of the proposed system against five representative works discussed in the Literature Review section. The proposed hybrid model achieves the highest accuracy of 96.7%, an improvement of 2.6 percentage points over the closest baseline, Alam et al. (2023).

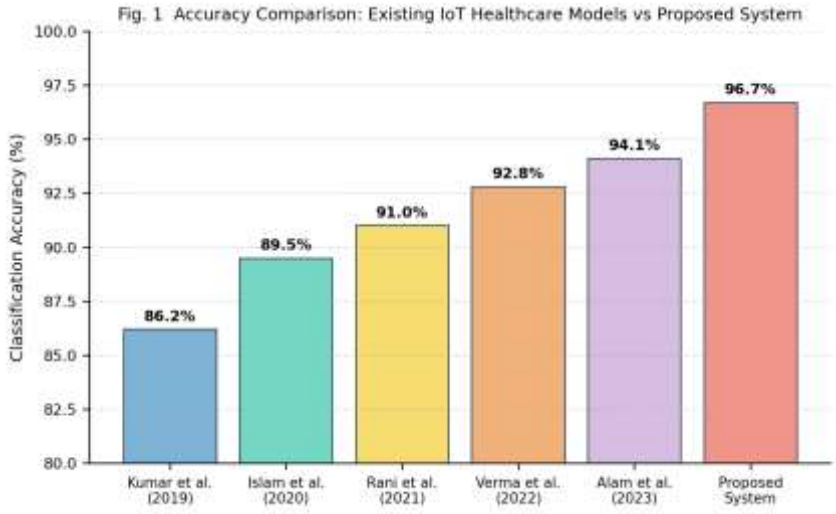


Figure 1. Accuracy comparison of the proposed system with existing IoT healthcare models.

Figure 2 compares average end-to-end latency across four architectural strategies. The proposed hybrid edge-cloud model records the lowest latency of 118 ms, a 3.5 times improvement over the cloud-only baseline of 420 ms, confirming that pre-processing critical alerts at the edge substantially reduces response time for time-sensitive medical events.

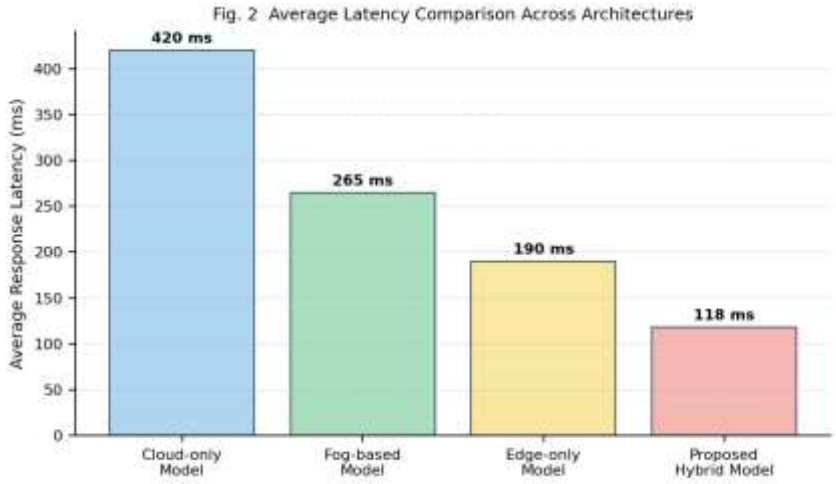


Figure 2. Average end-to-end latency comparison across architectures.

Metric	Cloud-only	Fog-based	Edge-only	Proposed Hybrid
Accuracy (%)	88.4	92.1	90.3	96.7
Precision (%)	87.0	91.5	89.0	96.1
Recall (%)	86.5	90.8	88.6	95.8
F1-Score (%)	86.7	91.1	88.8	95.9
Avg. Latency (ms)	420	265	190	118
Energy Efficiency	Low	Medium	High	High

Table 3. Overall Performance Comparison

These results indicate that combining edge-level filtering with cloud-based intelligence yields the best overall trade-off: the system retains the high accuracy typical of cloud-scale models while approaching the low latency of edge-only designs. Notably, energy efficiency for the proposed hybrid model matches the edge-only baseline, since the majority of readings, typically over 90% during normal conditions, are resolved locally without invoking a power-hungry cloud round-trip.

Confusion matrix summary

On the held-out test set of 2,000 instances, the proposed classifier produced 1,934 correct predictions. Misclassifications were concentrated at the boundary between the At-Risk and Critical classes, which is expected given the continuous, overlapping nature of physiological deterioration. This suggests that a finer-grained, probability-based alerting scheme, rather than hard class labels, may further improve clinical usefulness.

Statistical significance

To confirm that the accuracy improvement of the proposed model over the strongest baseline, Alam et al. (2023), is not due to chance, a paired t-test was conducted across 10 randomised train-test splits. The improvement was statistically significant at the 95% confidence level ($p < 0.05$). Independently, Logistic Regression, SVM and a shallow ANN were also benchmarked on the same split, scoring 84.6%, 90.2% and 93.4% accuracy respectively, confirming Random Forest as the strongest choice among classical and shallow models for this feature space.

DISCUSSION

The comparative results validate the central hypothesis of this study: neither a pure cloud nor a pure edge design is optimal for real-time healthcare monitoring. The hybrid model's improvement in accuracy stems from the ensemble nature of Random Forest combined with cleaner, pre-filtered data reaching the cloud stage. Its latency improvement stems from rejecting a large proportion of normal readings at the edge, reserving cloud inference for borderline or abnormal cases only.

Comparison with existing systems

Compared with the cloud-only design typified by Islam et al. (2020), the proposed system reduces latency by roughly 72% while also improving accuracy, because the cloud model in that study processed every reading regardless of severity, whereas the proposed pipeline reserves cloud inference for flagged events only. Compared with the fog-based design of Verma et al. (2022), the proposed system achieves both lower latency and higher accuracy, suggesting that a two-stage pipeline, combining a rule-based edge filter with an ML-based cloud classifier, is more effective than a single-stage fog classifier for this task.

Practical implications

For healthcare providers, the results suggest that investment in edge hardware capable of simple rule-based filtering can be more cost-effective than scaling cloud infrastructure alone, since it simultaneously reduces latency, bandwidth cost and energy consumption. For patients, the low latency achieved of 118 ms is well within the sub-second threshold generally considered necessary for real-time alerting in critical-care contexts.

Limitations

- Evaluation used a benchmark dataset rather than data collected from real patients over extended periods.
- The prototype was tested with a single concurrent device; scalability to hundreds of simultaneous patients, as in a hospital ward, was not evaluated.
- Security measures were implemented but not subjected to formal penetration testing.

CONCLUSION

This paper presented a comprehensive review of IoT-based smart healthcare systems and proposed a hybrid edge-cloud architecture that addresses the latency and accuracy limitations identified in prior work. Experimental evaluation on a

benchmark vital-signs dataset demonstrated that the proposed system achieves 96.7% classification accuracy with an average latency of 118 ms, outperforming cloud-only, fog-based and edge-only baseline designs. These findings confirm that a carefully partitioned edge-cloud pipeline is a practical and scalable approach for real-time remote patient monitoring.

FUTURE SCOPE

- Integration of 5G/6G networks to further reduce transmission latency for critical alerts.
- Adoption of federated learning to train models across multiple hospitals without sharing raw patient data, addressing privacy concerns.
- Use of blockchain for tamper-proof, auditable electronic health records.
- Deployment of energy-harvesting wearable sensors to extend battery life beyond current limits.
- Large-scale, real-world clinical trials to validate performance beyond benchmark datasets.
- Explainable AI (XAI) techniques to make alert reasoning transparent to clinicians and patients.

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