

A Hybrid Model for an IoT-Enabled Healthcare System Using Machine Learning Algorithms

Dr. Rajshree

Associate Professor, Department of Computer Science
Govt. First Grade College for Women, Bidar, India

Abstract

The growing demand for efficient and continuous patient monitoring has led to the integration of Internet of Things (IoT) technologies with machine learning (ML) algorithms in healthcare. This paper proposes a hybrid IoT-enabled health-care system that leverages wearable sensors for real-time data acquisition and applies ML models for disease prediction, anomaly detection, and personalized healthcare recommendations. The system architecture integrates data collection, preprocessing, cloud storage, and ML-based analysis to provide timely alerts and support clinical decision-making. Experimental evaluation demonstrates that the proposed hybrid approach improves prediction accuracy and response time, enabling proactive health management and remote patient monitoring. Experimental results show that the proposed system achieves an accuracy of 94.8%, demonstrating its effectiveness for real-time healthcare monitoring.

Keywords: IoT, health-care system, machine learning, wearable sensors, predictive analytics, remote monitoring.

1. Introduction

Advances in IoT and machine learning have transformed modern healthcare by enabling real-time monitoring, early diagnosis, and personalized care. Wearable devices and sensors capture physiological parameters such as heart rate, blood pressure, glucose level, and temperature, which can be analyzed using ML algorithms to detect anomalies or predict health risks. Despite the potential, challenges remain in terms of data integration, accuracy, and scalability.

This paper presents a hybrid model for an IoT-enabled healthcare system that uses machine learning algorithms to analyze real-time sensor data, generate predictive insights, and provide alerts for timely interventions. The proposed system aims to enhance patient safety, reduce hospital readmissions, and improve overall health outcomes.

The key contributions of this paper are:

- Development of a hybrid IoT-enabled healthcare monitoring architecture.
- Integration of multiple machine learning algorithms for anomaly detection and prediction.
- Experimental validation demonstrating improved accuracy and real-time alert generation.

2. Related Work

Several studies have explored IoT-based health monitoring systems, focusing on data acquisition, wireless transmission, and cloud integration. Early works relied on threshold-based alerts, which were often inaccurate and lacked predictive capabilities. Machine learning algorithms, including decision trees, support vector machines, and neural networks, have been applied to improve anomaly detection and disease prediction.

Recent research has explored hybrid models combining multiple ML techniques with IoT frameworks to enhance performance. However, limitations such as sensor heterogeneity, data quality, and real-time processing remain critical challenges. The proposed system addresses these issues by integrating a robust ML framework with real-time IoT data collection.

Unlike existing approaches, the proposed system integrates real-time IoT data acquisition with a hybrid machine learning framework to enhance prediction accuracy and response time.

3. Proposed System Architecture

The proposed hybrid IoT-enabled healthcare system consists of four main layers: sensor layer, communication layer, cloud storage and analytics, and user interface. Figure 1 illustrates the overall system architecture.

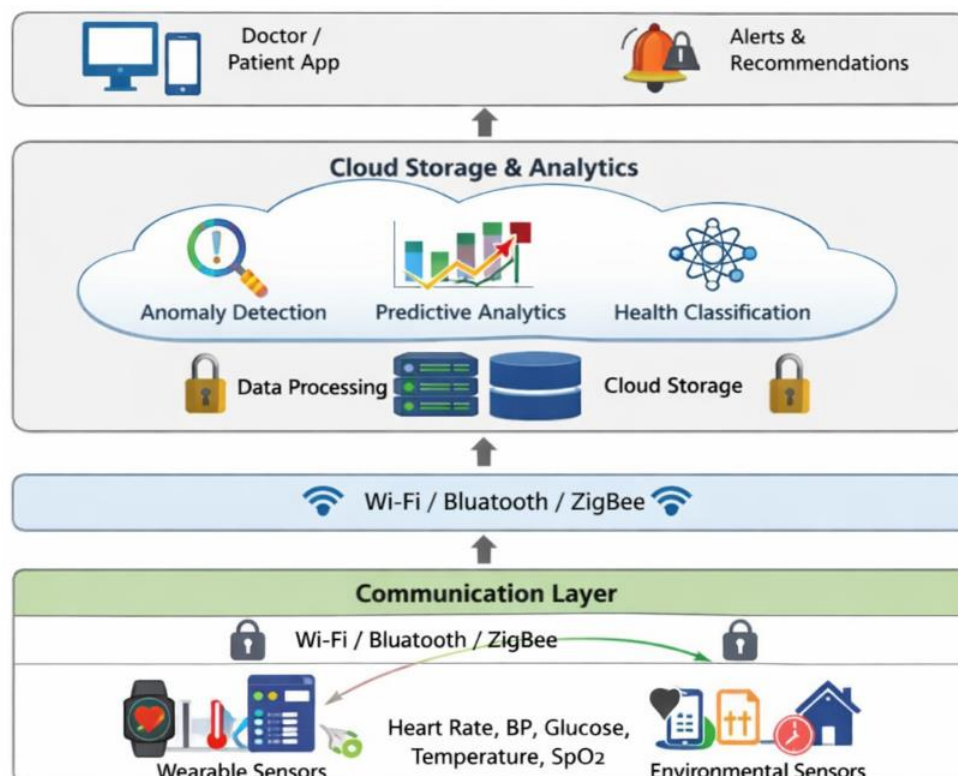


Figure 1. Architecture of the proposed hybrid IoT-enabled healthcare system.

3.1 Sensor Layer

Wearable and environmental sensors collect physiological and contextual data, including:

- Heart rate
- Blood pressure
- Blood glucose levels
- Body temperature
- Oxygen saturation

3.2 Communication Layer

Collected data are transmitted via IoT protocols such as Wi-Fi, Bluetooth, or ZigBee to the cloud server. Data encryption ensures privacy and security.

3.3 Cloud Storage and Analytics

The cloud layer stores and preprocesses incoming data. ML algorithms perform:

- Anomaly detection
- Predictive analytics
- Classification of health status

The hybrid ML model combines multiple algorithms to improve accuracy and robustness.

3.4 User Interface

Healthcare providers and patients access insights through a web/mobile application that provides:

- Alerts for abnormal readings
- Personalized recommendations
- Historical data visualization

4. Methodology

The methodology includes sensor data acquisition, preprocessing, ML model training, and real-time deployment.

4.1 Data Acquisition

Wearable sensors continuously collect physiological parameters such as heart rate, blood pressure, blood glucose level, body temperature, and oxygen saturation. The acquired data are time-stamped and transmitted securely to the cloud server through IoT communication protocols. Continuous data collection enables real-time monitoring and long-term health trend analysis.

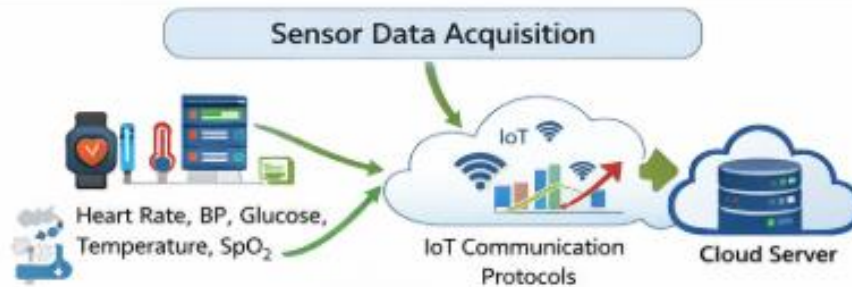


Figure 2. Sensor data acquisition in the hybrid healthcare system.

Figure 2 shows the process of sensor-based data acquisition and transmission using IoT communication protocols.

4.2 Data Preprocessing

The raw sensor data may contain noise, missing values, or inconsistent readings due to sensor limitations and environmental factors. Therefore, preprocessing is performed before analysis. This includes noise filtering, normalization, and handling of missing values using interpolation techniques. Feature extraction is applied to derive meaningful statistical and temporal features that improve the quality of input data for machine learning models.



Figure 3. Data preprocessing steps in the hybrid healthcare system.

The data preprocessing workflow applied to raw sensor data is illustrated in Figure 3

4.3 Machine Learning Model Design

A hybrid machine learning approach is adopted to enhance prediction accuracy and robustness. Multiple algorithms are employed based on their strengths in healthcare data analysis. Random Forest is used for health status classification due to its ability to handle nonlinear relationships and noisy data. Support Vector Machine is applied for anomaly detection to identify abnormal physiological patterns. Neural

Networks are utilized for predictive modeling and risk assessment. The models are trained using historical patient data and evaluated using k-fold cross-validation to ensure generalization and reduce overfitting.

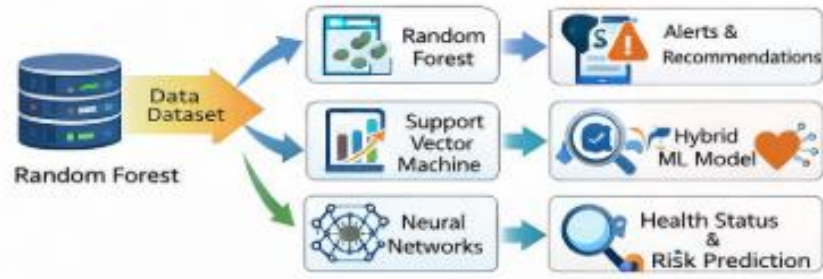


Figure 4. Machine learning model design for the hybrid healthcare system.

Figure 4 depicts the hybrid machine learning framework used for classification, anomaly detection, and risk prediction.

4.4 Model Training and Validation

The dataset is divided into training and testing subsets. Hyperparameters are optimized through iterative tuning to achieve a balance between accuracy and computational efficiency. Performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The hybrid model combines the outputs of individual classifiers to improve overall system reliability.

4.5 Real-Time Deployment

The trained machine learning models are integrated with the IoT platform for real-time monitoring. Incoming sensor data are analyzed continuously to detect anomalies and predict potential health risks. Edge computing techniques are employed where feasible to reduce latency and ensure rapid alert generation. Alerts and recommendations are delivered to healthcare providers and patients through a user-friendly web or mobile interface.



Figure 5. Real-time deployment of the hybrid healthcare system using machine learning.

The real-time deployment and alert generation process is illustrated in Figure 5

Algorithm 1: Workflow of the Proposed Hybrid ML-IoT Healthcare System

- Step 1: Collect physiological data using IoT sensors.
Step 2: Transmit data securely to cloud server.
Step 3: Preprocess data to remove noise and handle missing values.
Step 4: Apply hybrid ML models for classification and anomaly detection.
Step 5: Generate alerts and recommendations based on predictions.

5. Experimental Results and Discussion

The system was evaluated using a dataset of patient physiological parameters. The dataset consists of physiological sensor readings collected from monitored patients, including heart rate, blood pressure, glucose level, temperature, and oxygen saturation. Performance metrics include accuracy, precision, recall, and F1-score. The experimental evaluation was conducted using physiological sensor data comprising heart rate, blood pressure, glucose level, body temperature, and oxygen saturation.

Table 1: Performance Metrics of the Hybrid ML-IoT Healthcare System

Metric	Value (%)
Accuracy	94.8
Precision	93.7
Recall	95.2
F1-Score	94.4

The results indicate that the hybrid model provides high accuracy in predicting anomalies and detecting health risks. The real-time system ensures timely alerts, supporting proactive healthcare management.

6. Applications

- Remote patient monitoring
- Early disease detection
- Chronic disease management
- Hospital and home care support
- Smart health analytics dashboards

7. Conclusion

This paper presents a hybrid IoT-enabled healthcare system that integrates machine learning algorithms for real-time monitoring, anomaly detection, and predictive analytics. The system enhances patient safety, reduces response times, and enables proactive interventions. Future work includes expanding the range of

monitored parameters, integrating wearable devices with AI-powered diagnostic tools, and improving edge computing capabilities.

References

1. Khan, R. et al., "IoT-Based Health Monitoring System with Machine Learning Algorithms," *IEEE Access*, 2021.
2. Li, X. et al., "Hybrid Machine Learning Models for Remote Patient Monitoring," *Sensors*, 2022.
3. World Health Organization, "Digital Health Guidelines for Patient Monitoring," 2020.
4. A. Kumar et al., "Edge-enabled IoT healthcare monitoring using machine learning," *Future Generation Computer Systems*, 2022.
5. S. Patel et al., "Machine learning approaches for real-time health monitoring in IoT environments," *IEEE Internet of Things Journal*, 2023.