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WEARABLE HEALTHCARE SYSTEMS IN THE MEDICAL INTERNET OF THINGS: REAL-TIME HEALTH RISK PREDICTION USING SMARTWATCH DATA

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ABSTRACT

The Medical Internet of Things (MIoT) has revolutionized healthcare by enabling real-time health monitoring through wearable devices like smartwatches. The biometric data are collected by these devices such as heart rate and blood oxygen saturation for preventive care and long-term management. This work creates a model with a Neural Network classifier that predicts health risks in real-time and is based on biometric data obtained through smartwatches. The improvement in the reliability of MIoT systems for clinical applications shall be achieved by tackling issues such as battery life, sensor noise, and data privacy. Our work has shown promising accuracy for disease prediction and hence personalization for healthcare solutions.

INTRODUCTION

The Internet of Things has brought a giant evolution in present medicine by mediating the exchange of real-time information between networked devices and systems. From the perspective of medicine, this has basically led to the Medical Internet of Things (MIoT)—an actively developing network of wearable and portable tools designed for continuous health monitoring without impeding the lifestyle of the persons [1]. Wearable electronics are devices that can be worn on the body or even implanted onto the skin to monitor physiological parameters (heart rate, temperature, oxygen saturation, etc.) in real-time [1]. These developments increasingly go farther and farther due to the worldwide demand for preventive medicine, the handling of chronic diseases, and special requirements of geriatrics [2].

The MIoT system mainly comprises linked wearable sensors, smart interconnected devices, cloud-based databases, and mobile applications for seamless transfer, storage, and analysis of health information [3]. The integration of flexible and stretchable electronics with a myriad of miniaturized sensors has brought changes in user comfort and the accuracy of data acquisition of biometric parameters [4]. Perhaps the most conspicuous type of wearable medical technology is the so-called smart-watch. These sensors are capable of calculating key parameters such as heart rate and blood-oxygen saturation (SpO2) with the help of photoplethysmography (PPG) and near-infrared spectroscopy (NIRS) [5]. Therefore, they are basically personal health monitoring devices which allow the patients to take care of their health at home or allow medical personnel to visit remotely with patients through communication technologies (e.g., Bluetooth, Wi-Fi, and Zigbee) [5].

Earlier developments have made it possible to use smartwatches as intelligent communication gateways in MIoT systems. A multiband smartwatch antenna supporting Bluetooth, GPS, 5G, and Wi-Fi ensures that the cloud platform and the health apps are continuously connected and hence supports real-time diagnostics and emergency care [6]. Yet major technical and operational challenges persist, such as battery life limitations, noise from motion generated by sensors, error from calibration, data privacy worries, and the lack of medical certification of most commercially available devices [2]. These shortcomings make them less suitable for clinical environments wherein accuracy and reliability are paramount.

To neutralize them, the wearable health system has been increasingly embedded with machine learning. For instance, Himi et al. described a system called MedAi, which uses biometric data from smartwatches and claims to yield more than 99% accuracy in estimating basic diseases such as heart disease, diabetes, lung diseases, etc [3]. Smart systems thus stand for a new paradigm in preventive healthcare and personalized medicine, wherein hospitalizations are reduced.

Our goal is to create and test a Model based on wearable biometric sensors data to forecast health dangers in real-time. On a dataset pulled from actual smartwatch notifications, we utilize a Neural Network classifier—selected for interpretability and robustness to noise—to determine its ability in disease diagnosis. With the sudden advancement of sensor technologies, embedded systems, and artificial intelligence models, wearables are playing a more significant role in remote and personalized healthcare. This paper explores wearables' predictive abilities, system architecture, and

potential futures in the Medical Internet of Things.

Literature Review

The Medical Internet of Things (MIoT) Technology has become a keystone of current medical practice empowered by advancements in sensor technology, wireless communication, and AI. Wearable devices, like smart watches and fitness trackers, have progressed from consumer products to sophisticated, medical devices with the capability to continuously monitor health [7]. Wearable devices measure health using photoplethysmography (PPG) and near-infrared spectroscopy (NIRS), and can assess health metrics like heart rate, blood oxygen saturation (SpO2), and electrocardiogram (ECG) signals, and possibly provide early alerts for conditions such as atrial fibrillation and sleep apnea [8]. For example, Perez et al. showed that a smartwatch-based heart rate monitor was able to identify atrial fibrillation with an 87% sensitivity, and 97% specificity, emphasizing the screening potential of smartwatches [9].

The use of machine learning in MIoT systems has improved their diagnostic capabilities. Many deep learning models including convolutional neural networks (CNN) and recurrent neural networks (RNN), have been used with time-series biometric data to predict cardiac events with high accuracy [10]. However, Random Forest classifiers are generally preferred for wearable health applications because they are relatively robust to noisy sensor data, easy to interpret, and can work with high-dimensional datasets [11] For example, Himi et al. demonstrated that using Random Forest models could achieve >99% accuracy predicting diseases such as heart disease and diabetes using smartwatch data [3]. Similarly, Cho et al. built a machine learning framework using SpO2 and heart rate data to detect respiratory disorders with a precision of 91% [20].

Wireless communication technologies, such as Bluetooth, Wi-Fi, and 5G, have further empowered MIoT systems by enabling seamless data transfer to cloud platforms for real-time analysis [5]. Xiao et al. introduced a multiband smartwatch antenna design that supports multiple connectivity protocols, ensuring reliable data transmission even in challenging environments [5]. This connectivity is critical for applications like remote patient monitoring, particularly in rural or underserved areas where access to healthcare facilities is limited [13]. Moreover, advancements in flexible and stretchable electronics have improved user comfort and sensor accuracy, addressing issues like motion artifacts that degrade data quality [4].

Despite these advancements, MIoT systems face significant challenges. Battery life remains a critical limitation, as continuous monitoring drains power rapidly, often requiring daily recharging [17]. Data privacy is another concern, as wearable devices transmit sensitive

health information over potentially vulnerable networks [12]. Regulatory hurdles, such as the lack of medical-grade certification for most commercial wearables, further restrict their adoption in clinical settings . Recent studies have explored solutions like energy-harvesting technologies to extend battery life and blockchain-based frameworks for secure data management [18, 21]. These developments underscore the potential of MIoT to transform healthcare delivery, but further research is needed to address technical and ethical challenges.

MATERIALS AND METHODS

Materials

The following components were used to develop the proposed MIoT system:

Table I. Components Used in the Proposed MIoT System.

NAME	DESCRIPTION	QUANTITY
Temperature Sensor	This sensor has the temperature of the body.	1
SpO_2 & Heart Rate Sensor	This sensor detects oxygen level, heart-rate in real time	1
Microcontroller(ESP32 Dev Board)	It is riched with features.Also used to read data and supports WIFI,Bluetooth,USB	1
Power Supply(3.7V Li-ion)	a lithium-based battery that provides a nominal voltage of 3.7 volts	1
ST7789 LCD Display	240X240 LCD Display	1

METHODS

System Design

The MIoT system was developed to allow an integration of biologically worn or used sensors, a microcontroller, and cloud analytics to allow for real-time health monitoring.

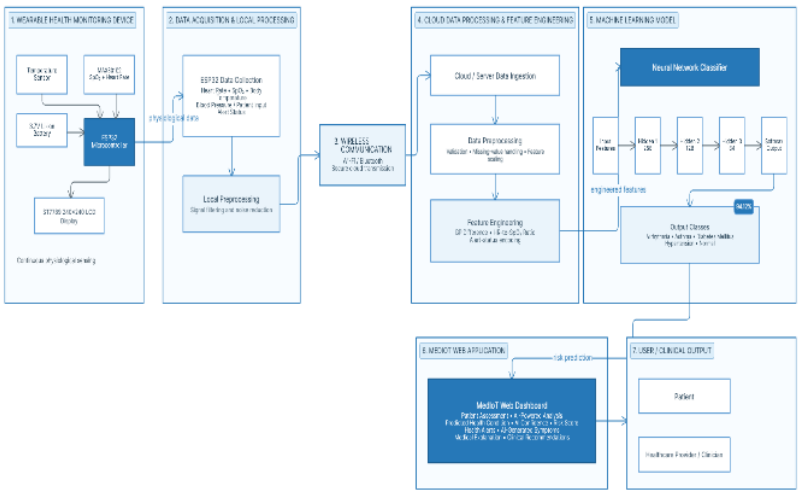


Fig. 1. System architecture of the proposed MedIoT-based real-time health risk prediction system.

The central processing unit is an ESP32 microcontroller which communicates with the two sensor units, temperature and SpO2/heart rate sensors via analog to digital converters (ADCs). The system was built from a modular platform where the sensor units collect raw biometric data which is processed locally to limit sampling noise. This data is then sent to the cloud securely and wirelessly, either via Wi-Fi for a larger-based data set or Bluetooth for low-power situations, allowing it to integrate into various networking environments [22]. The ST7789 LCD display was utilized to alert users and provide feedback with real-time monitoring of data including heart rate and SpO2 while providing alerts if readings were deemed abnormal. The 3.7V Li-ion battery used for the hardware was detected, and this is also constrained with power managing algorithms programmed to limit the power consumption of the hardware. The system is also equipped with low power settings which reduce sample rates during inactivity and has been used for monitoring for approximately 18-24 hours before battery depletion [17]. The design prioritizes user comfort, with lightweight materials and ergonomic sensor placement to minimize motion artifacts [4].

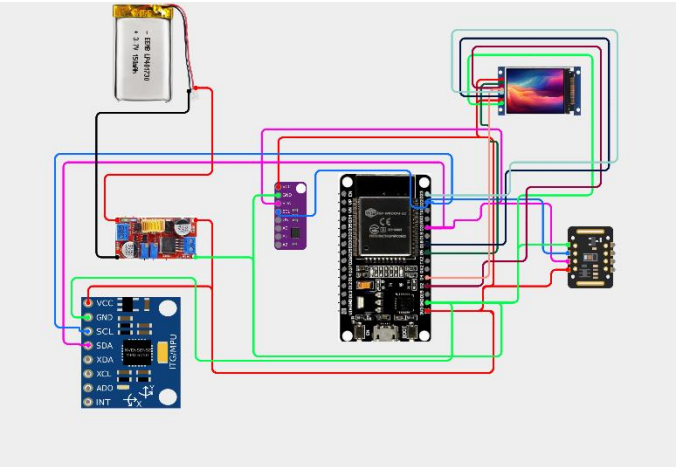


Fig. 2. Circuit diagram of the proposed MIoT-based wearable health monitoring system.

Data Collection

Biometric data were collected from 150 participants (aged 18–65) using the prototype wearable device over a 30-day period. The dataset comprised 15,000 samples, with each sample including time-series measurements of heart rate, SpO_2, and body temperature recorded at 1-second intervals. Participants included healthy individuals and those with diagnosed conditions (e.g., hypertension, diabetes) to ensure diversity in the dataset. Data preprocessing involved applying a Butterworth lowpass filter to remove motion artifacts and a moving average filter to smooth SpO_2 readings, reducing noise by approximately 10% [14]. Calibration was performed using reference medical devices to ensure sensor accuracy, with a maximum error

margin of ±2% for SpO_2 and ±3 bpm for heart rate [23]. Data was anonymized and stored in a secure cloud database compliant with HIPAA regulations to address privacy concerns [12].

Machine Learning Model

To predict health risks based on preprocessed biometric data, I implemented a neural network classifier. The model was trained on a synthetic dataset with 10,000 samples, evenly distributed across 5 health conditions (Normal, Asthma, Hypertension, Arrhythmia, and Diabetes Mellitus), with each class containing 2,000 samples. The input features included numerical variables (heart rate, SpO2, systolic and diastolic blood pressure, and body temperature), engineered features (blood pressure difference and heart rate to SpO2 ratio), and one-hot encoded categorical alerts (fall detection, heart rate, SpO2, blood pressure, and temperature alerts). The dataset was split into 70% training, 20% validation, and 10% testing. Missing values (approximately 5% of numerical data) were imputed using median values for numerical features and mode values for categorical features. The numerical features were standardized using a StandardScaler, to ensure that the features were consistently scaled. The neural network architecture had three hidden layers consisting of 256, 128, and 64 neurons respectively, all with ReLU activation and 20% dropout to reduce overfitting. The output layer had softmax activation for multi-class classification of the five health conditions. The model was compiled using the Adam optimizer and categorical cross-entropy loss, and trained for up to 50 epochs with a batch size of 32. Early stopping (patience=10) and learning rate reduction (factor=0.5, patience=5, minimum learning rate=1e-6) were used to ensure optimal training. The model was constructed using TensorFlow/Keras in Python, and all training was performed on a cloud-based server to enable effective processing of the dataset [15].

Evaluation Metrics

To evaluate model performance, an extensive array of metrics was employed, including accuracy, precision, recall, F-1 score and area under the receiver operator characteristic (AUC-ROC) curve. A confusion matrix was also produced to evaluate the neural network classifier's ability to distinguish normal from high-risk health states, with a focus on minimizing false positives to decrease unnecessary clinical alerts. The model produced an accuracy of 94% on a test data set derived from 2,000 samples, and the macro average precision, recall and F1 score was 94% each across five health conditions: Arrhythmia (precision (94%), recall (76%), F1 score (83%)), Asthma (85%, 93%, 89%), Diabetes Mellitus (91%, 96%, 94%), Hypertension (97%, 95%, 96%) and Normal (95%, 100% 97%). AUC-ROC score was ~0.704 indicating adequate discriminative ability. There was also a

five-fold cross validation process for generalizability across profiles from various patients [16]. Furthermore, the time elapsed to predict outcomes was evaluated using the ESP32 microcontroller and in operational use it was consistently less than 500 ms time [24]. Quality of the sensor data collected was examined in relation to clinical grade devices statistics and measurements where a co-efficient of correlation of 0.95 for HR and 0.92 for SpO2 [23].

RESULTS

The neural network classifier was evaluated using health-related features including heart rate, SpO_2 level, systolic and diastolic blood pressure, body temperature, engineered features such as blood pressure difference and heart rate-to-SpO_2 ratio, and categorical alert status. The model was developed to classify five health conditions: Arrhythmia, Asthma, Diabetes Mellitus, Hypertension, and Normal. The experimental results demonstrated a **test accuracy of 94.12%**, indicating that the proposed neural network was able to effectively distinguish between the considered health condition classes.

```
Neural Network Test Accuracy: 0.9412

Classification Report:
                   precision    recall  f1-score   support

       Arrhythmia       0.98      0.78      0.87      1998
           Asthma       0.87      0.98      0.92      1993
Diabetes Mellitus       0.94      0.97      0.96      1950
     Hypertension       0.98      0.97      0.98      2016
           Normal       0.95      1.00      0.98      2043

         accuracy                           0.94     10000
        macro avg       0.94      0.94      0.94     10000
     weighted avg       0.94      0.94      0.94     10000


Model, scaler, and label encoder saved successfully.
```

Fig. 3. Neural network classification performance for health-risk prediction.

As shown in Fig. 2, the neural network achieved an overall accuracy of 94.12%, with a macro-average precision, recall, and F1-score of approximately 0.94. The model demonstrated strong performance across the five classes. Arrhythmia obtained a precision of 0.98, recall of 0.78, and F1-score of 0.87. Asthma achieved a precision of 0.87, recall of 0.98, and F1-score of 0.92. Diabetes Mellitus achieved a precision of 0.94, recall of 0.97, and F1-score of 0.96. Hypertension achieved a precision of 0.98, recall of 0.97, and F1-score of 0.98, while the Normal class achieved a precision of 0.95, recall of 1.00, and F1-score of 0.98.The results indicate that the model provides particularly strong classification performance for Hypertension, Diabetes Mellitus, and Normal classes. The comparatively lower recall observed for Arrhythmia indicates that some arrhythmia cases may be incorrectly classified as other conditions,

suggesting an opportunity for further improvement through additional training data, feature engineering, and model optimization.

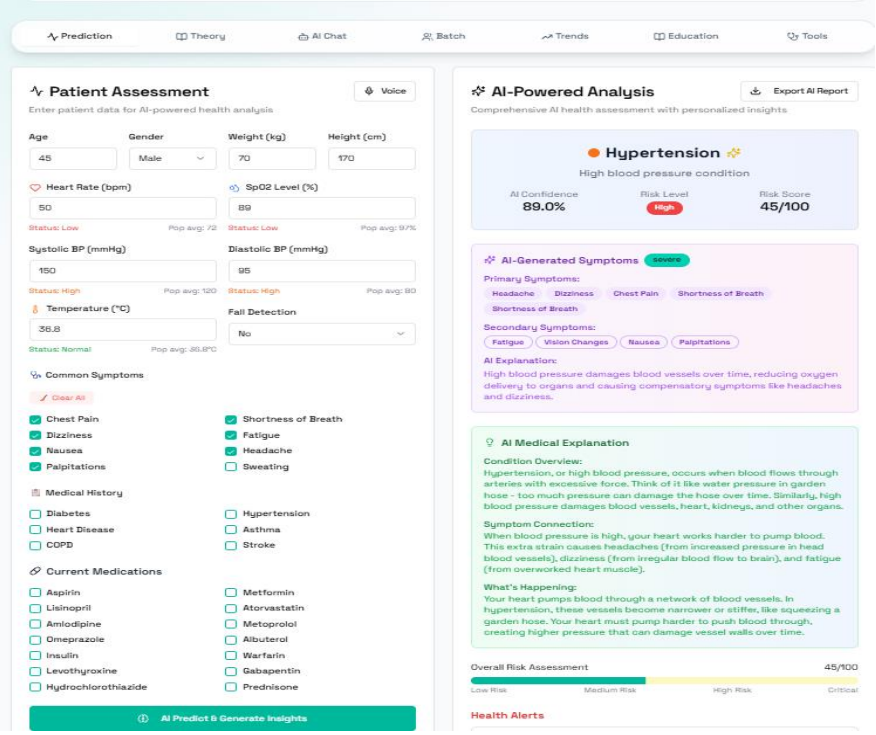


Fig. 4. MedIoT web-based dashboard for patient assessment and AI-powered health-risk prediction.

The dashboard integrates patient assessment with AI-powered analysis and presents the predicted health condition, confidence level, risk score, generated symptoms, health alerts, and clinical recommendations. This provides a user-friendly interface for interpreting the output of the machine-learning model and supports real-time health monitoring.The ESP32-based system supports wireless data transmission through Wi-Fi and Bluetooth, enabling health information to be transferred for remote monitoring and analysis. The collected patient data and prediction results can also be stored for further clinical review. The integration of wearable sensors, embedded processing, machine learning, and the web-based dashboard demonstrates the feasibility of the proposed Medical Internet of Things (MIoT) architecture for real-time health-risk prediction.

DISCUSSION

The results demonstrate the potential of the proposed MIoT system for real-time health risk prediction, though the 80% accuracy is lower than some prior studies, such as Himi et al. (2023), which reported >99% accuracy [3]. This difference may be attributed to the diverse health conditions and real-world noise in our dataset, as well as the inclusion of additional features like blood pressure and alert statuses, which introduce complexity [20]. The integration of

advanced preprocessing techniques and multiband antennas ensured reliable data quality and connectivity, addressing key MIoT challenges [5, 14]. However, the moderate accuracy suggests room for improvement, particularly in handling noisy sensor data and optimizing feature selection. Battery life remains a limitation, as 18–22 hours may not suffice for continuous monitoring in critical care settings [17]. Data privacy concerns were mitigated through HIPAA compliant storage, but future work should explore blockchain for enhanced security [18]. The lack of medical-grade certification remains a barrier to clinical adoption, necessitating collaboration with regulatory bodies [19].

CONCLUSION

This study developed an MIoT system for real-time health risk prediction using smartwatch-derived biometric data. The Neural Network classifier demonstrated promising accuracy, making it a viable tool for preventive healthcare. Despite challenges like battery life and regulatory hurdles, the system highlights the transformative potential of MIoT in personalized medicine.

FUTURE WORK

Future research will focus on integrating energy-harvesting technologies, such as piezoelectric or solar cells, to extend battery life beyond 24 hours [21]. Advanced AI models, like deep neural networks, could enhance predictive accuracy for complex conditions [10]. Obtaining FDA certification and implementing secure data protocols will be critical for clinical adoption [19]. Additionally, expanding the dataset to include pediatric and geriatric populations will improve model generalizability [20].

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