Real Time Vital Sign Monitoring Using AI Enabled Wearables

***Gajendran, **Dr. S. Bhargavi Latha**
*Post Graduate Student, **Associate Professor
Reva University, Bengaluru, India

[1]*Received: 21/05/2026; Accepted: 25/06/2026; Published: 09/07/2026*

Abstract

Real-time monitoring of physiological parameters plays a significant role in improving healthcare by enabling the early identification of abnormal health conditions. This paper presents an intelligent wearable health monitoring system that integrates Internet of Things (IoT) technology with Quantum Machine Learning (QML) for continuous health assessment. The proposed framework acquires electrocardiogram (ECG), body temperature, heart rate, and blood oxygen saturation (SpO_2) through wearable sensors interfaced with an Arduino-based platform. The acquired data are transmitted via a Wi-Fi module to a web application for real-time visualization and analysis. Prior to prediction, the sensor readings are normalized to improve data consistency. A Quantum Support Vector Classifier (QSVC) is employed to classify the health status as normal or abnormal. Experimental evaluation demonstrates that the proposed framework provides reliable prediction while supporting continuous remote monitoring, making it a promising solution for intelligent and accessible healthcare applications.

Keywords— *Internet of Things (IoT); Wearable Health Monitoring; Electrocardiogram (ECG); Quantum Machine Learning (QML); Quantum Support Vector Classifier (QSVC); Real-Time Health Monitoring; Health Status Prediction.*

1. Introduction

The rapid advancement of digital healthcare has accelerated the adoption of wearable sensing technologies for continuous monitoring of physiological parameters. Unlike conventional healthcare systems that rely on periodic clinical examinations, wearable devices enable real-time monitoring of vital signs, supporting early diagnosis, preventive healthcare, and personalized medical services. Recent developments in wearable sensors and wireless communication have significantly improved the reliability and accessibility of remote healthcare systems [1].

Wearable biosensors capable of measuring Electrocardiogram (ECG), heart rate, body temperature, and blood oxygen saturation (SpO_2) provide continuous physiological information for effective health assessment. When integrated with the Internet of Things (IoT), these sensors enable secure data transmission, remote accessibility, and real-time monitoring, thereby improving healthcare delivery and patient management [2], [3].

The increasing availability of physiological data has encouraged the adoption of Artificial Intelligence (AI) and Machine Learning (ML) techniques for automated health assessment and disease prediction. More recently, Quantum Machine Learning (QML) has emerged as a promising computational approach, with Quantum Support Vector Classifier (QSVC) models demonstrating encouraging performance in complex healthcare classification tasks [4].

Motivated by these advancements, this paper proposes a real-time vital sign monitoring framework that integrates wearable physiological sensors, Arduino-based data acquisition, ESP8266-enabled IoT communication, a Flask-based

[1] [1] *How to cite the article:* Gajendran, Latha S.B.; Real Time Vital Sign Monitoring Using AI Enabled Wearables; *International Journal of Advances in Engineering Research*, July 2026, Vol 32 Issue 1; pg: 1-14

web application, and a Quantum Support Vector Classifier (QSVC) for intelligent health status prediction. The proposed system continuously monitors ECG, heart rate, body temperature, and SpO_2 to classify physiological conditions into normal and abnormal states, thereby supporting efficient remote patient monitoring and timely clinical decision-making [5].

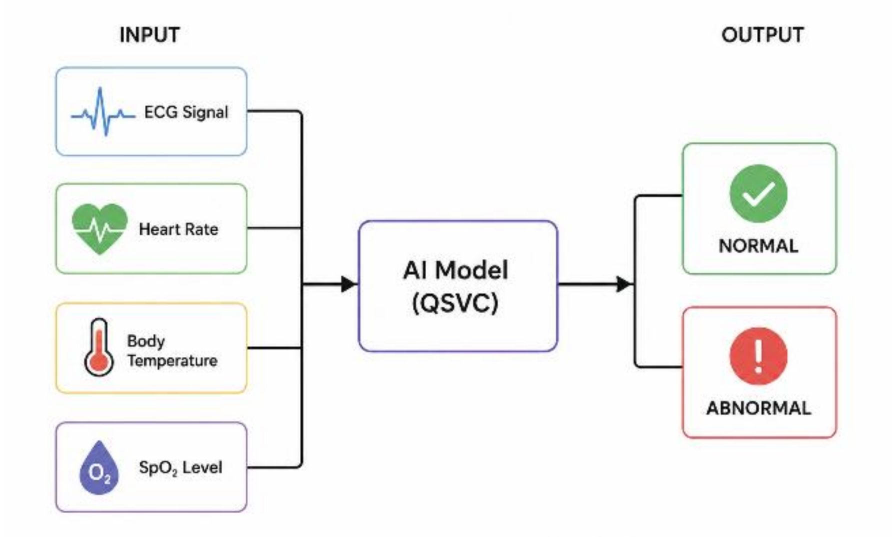

Fig. 1. Input–Output Representation

Fig. 1 illustrates the input–output representation of the proposed healthcare prediction framework, where multiple physiological parameters are provided as input to the QSVC model for predicting the patient's health status as either normal or abnormal. The increasing volume of physiological data generated by wearable devices has accelerated the adoption of Artificial Intelligence (AI) and Machine Learning (ML) techniques for automated health assessment and clinical decision support. Although conventional machine learning algorithms have demonstrated promising performance, they often encounter challenges in analysing complex biomedical datasets with high-dimensional features. Consequently, Quantum Machine Learning (QML) has emerged as a promising alternative for improving classification accuracy and computational efficiency in healthcare applications [6]. Recent studies have demonstrated that Quantum Support Vector Classifier (QSVC) models can effectively enhance biomedical data classification by exploiting quantum kernel-based learning methods [7].

Moreover, the integration of wearable sensing technologies with IoT communication and cloud-based monitoring platforms has enabled continuous remote healthcare services, allowing clinicians to access patient information in real time while improving the quality of healthcare delivery [8]. Nevertheless, the combined implementation of wearable sensors, IoT communication, cloud-assisted visualization, and Quantum Machine Learning within a unified healthcare framework remains relatively limited in current research [9].

Therefore, this paper proposes an intelligent real-time vital sign monitoring system that integrates wearable physiological sensors, Arduino-based data acquisition, ESP8266-enabled IoT communication, a Flask-based monitoring platform, and a Quantum Support Vector Classifier (QSVC) for automated health status prediction. The proposed framework aims to provide accurate, reliable, and real-time healthcare monitoring, thereby supporting early diagnosis and efficient remote patient management [10].

2. Related Work

Recent advancements in wearable healthcare technologies have significantly improved continuous physiological monitoring through lightweight and portable sensing devices. Modern wearable systems can measure multiple vital signs, including Electrocardiogram (ECG), heart rate, body temperature, and blood oxygen saturation (SpO_2), enabling continuous health assessment in both clinical and home environments. These systems contribute to early disease detection and enhance the quality of remote patient care. However, many existing wearable platforms primarily focus on physiological data collection without incorporating advanced intelligent decision-making mechanisms [11], [12].

The integration of the Internet of Things (IoT) has further strengthened remote healthcare by enabling seamless communication between wearable devices, cloud platforms, and healthcare professionals. IoT-based healthcare systems facilitate real-time data transmission, remote accessibility, and continuous patient monitoring, thereby improving healthcare efficiency and reducing the need for frequent hospital visits. Despite these advantages, several reported frameworks mainly concentrate on communication and cloud connectivity while offering limited support for intelligent health prediction and automated clinical analysis [13], [14].

Artificial Intelligence (AI) and Machine Learning (ML) have become essential technologies for analyzing biomedical data and supporting automated healthcare applications. Various supervised learning algorithms have been successfully employed for disease prediction, physiological signal classification, and anomaly detection. Although conventional ML models provide satisfactory prediction performance, their computational capability may be limited when processing complex and high-dimensional healthcare datasets, motivating the exploration of more advanced computational paradigms [15], [16].

Quantum Machine Learning (QML) has recently attracted considerable attention due to its potential to enhance classification performance through quantum computational techniques. Among various QML approaches, the Quantum Support Vector Classifier (QSVC) has demonstrated promising capability in solving complex classification problems using quantum kernel methods. Nevertheless, practical implementation of QSVC in real-time wearable healthcare systems remains limited, and further investigation is required to evaluate its effectiveness in intelligent health monitoring applications [17], [18].

The literature indicates that wearable sensing, IoT-based communication, Artificial Intelligence, and Quantum Machine Learning have been extensively investigated as individual research domains. However, only limited studies have integrated these technologies into a unified framework capable of performing continuous physiological monitoring and intelligent health status prediction. In particular, the application of Quantum Support Vector Classifier (QSVC) for real-time wearable healthcare remains relatively unexplored. To address this research gap, the proposed work integrates wearable physiological sensors, Arduino-based data acquisition, ESP8266-enabled IoT communication, a Flask-based web application, and QSVC-based health status classification into a single intelligent healthcare framework for continuous remote patient monitoring and timely clinical decision-making [19], [20].

Table 1 Comparative Analysis

Ref.	**Method / Technology**	**Key Contribution**	**Limitation**
[11]	Wearable Sensors + ML	Discussed wearable healthcare systems integrated with machine learning for continuous patient monitoring.	Limited emphasis on real-time intelligent prediction.
[12]	Intelligent Wearable Healthcare (Industry 5.0)	Proposed smart wearable healthcare architecture with intelligent monitoring capabilities.	Does not incorporate Quantum Machine Learning techniques.
[13]	IoT + ECG Classification	Developed an IoT-enabled ECG monitoring framework for remote healthcare applications.	Focused mainly on ECG data rather than multiple physiological parameters.

[14]	IoT + Deep Learning	Reviewed deep learning approaches for IoT-based healthcare applications.	Primarily survey-based without proposing an integrated implementation.
[15]	IoT + Machine Learning	Presented opportunities and challenges of AI-driven smart healthcare systems.	General discussion without a real-time wearable implementation.
[16]	AI-Based Health Prediction	Applied machine learning models for healthcare prediction and decision support.	Conventional ML models may face scalability issues with complex biomedical data.
[17]	Quantum Machine Learning	Proposed a QML-based framework for heart failure prediction.	Focused on disease prediction rather than continuous wearable monitoring.
[18]	QSVC-Based Heart Disease Prediction	Demonstrated improved prediction using Quantum Support Vector Classifier.	Did not integrate IoT communication or wearable devices.
[19]	Quantum Neural Network & QSVM	Evaluated quantum models for healthcare classification tasks.	Limited validation on real-time physiological sensor data.
[20]	Wearable Sensors + IoT + Flask + QSVC	Integrates wearable physiological sensors, Arduino, ESP8266, Flask web application, and QSVC for real-time intelligent health monitoring.	Designed to overcome the limitations identified in previous studies.

3. Proposed Methodology

This study proposes an AI-enabled wearable healthcare framework for continuous monitoring of physiological parameters and intelligent health status prediction. The proposed framework integrates wearable biosensors, Arduino-based data acquisition, ESP8266-enabled IoT communication, a Flask-based web application, and a Quantum Support Vector Classifier (QSVC) to provide real-time remote health monitoring. The overall workflow is designed to acquire physiological signals, transmit them securely through an IoT network, analyze the collected data using quantum machine learning, and display the prediction results through a web-based dashboard.

3.1 System Architecture

The overall architecture of the proposed system consists of four major modules: physiological data acquisition, IoT communication, intelligent data processing, and real-time visualization. Initially, wearable sensors continuously measure Electrocardiogram (ECG), heart rate, body temperature, and blood oxygen saturation (SpO_2). The acquired sensor values are processed by an Arduino Uno, which serves as the central data acquisition unit. The processed information is transmitted through the ESP8266 Wi-Fi module to the cloud environment, where data preprocessing and intelligent classification are performed using the Quantum Support Vector Classifier (QSVC). Finally, the prediction results are displayed through a Flask-based web application, enabling continuous remote monitoring of patient health conditions. Fig. 2 illustrates the overall architecture of the proposed AI-enabled wearable healthcare monitoring framework.

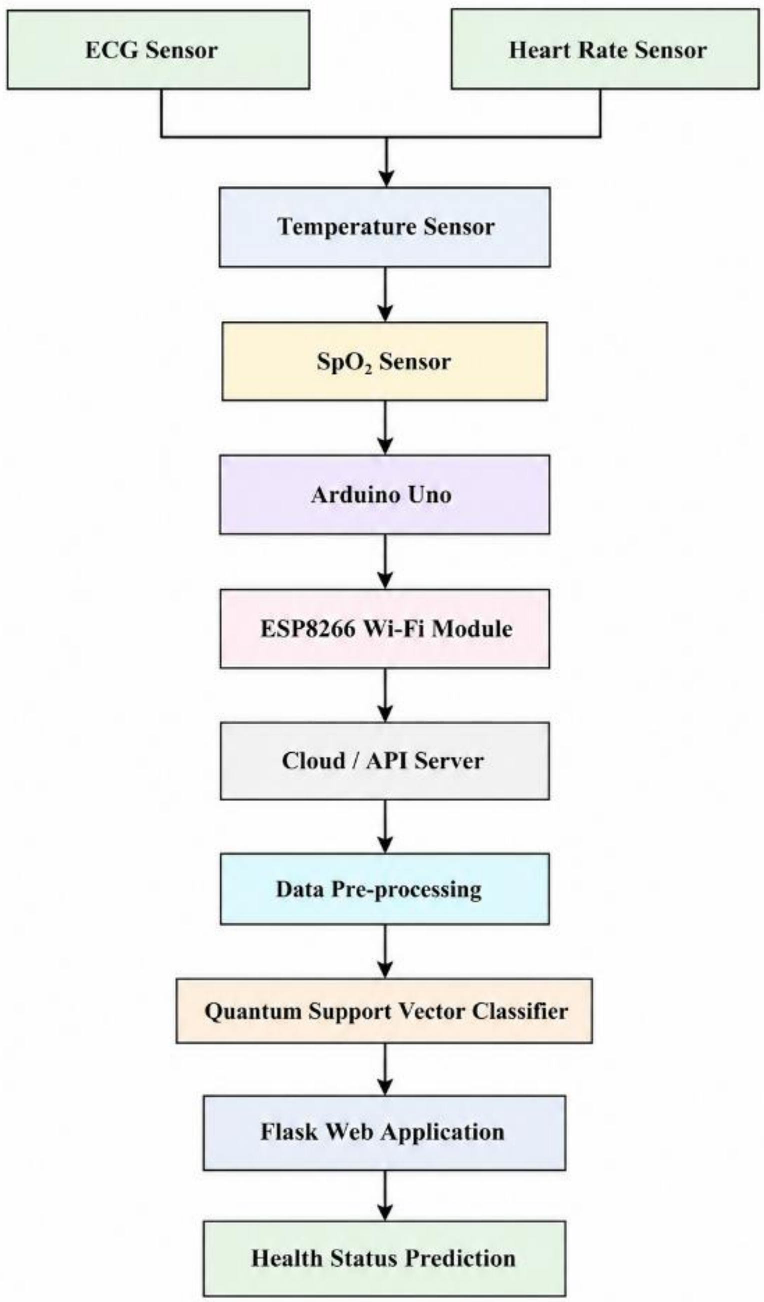

Fig. 2. Overall Architecture

3.2 Data Acquisition and IoT Communication

The wearable sensing module continuously acquires physiological parameters required for intelligent health assessment. ECG, heart rate, body temperature, and SpO_2 measurements are collected using dedicated biomedical sensors connected to the Arduino Uno. The collected sensor readings are validated before being transmitted through the ESP8266 communication module to the cloud environment for further processing and classification. Table 1 summarizes the physiological parameters employed in the proposed healthcare monitoring framework.

Table 2. Physiological Parameters Used in the Proposed System

Parameter	Sensor	Purpose
ECG	ECG Sensor	Cardiac activity monitoring
Heart Rate	Heart Rate Sensor	Pulse measurement
Body Temperature	Temperature Sensor	Body temperature monitoring
SpO_2	Pulse Oximeter Sensor	Blood oxygen saturation monitoring

The physiological parameters presented in Table 2 serve as the primary input features for the QSVC model, facilitating accurate health status prediction.

3.3 Quantum Support Vector Classifier (QSVC)

The collected physiological parameters are preprocessed and transformed into a quantum feature space prior to classification. The QSVC model utilizes quantum kernel techniques to capture nonlinear relationships among physiological features and accurately distinguish normal and abnormal health conditions.

The quantum feature mapping process is represented as

$$x \rightarrow | \phi(x)\rangle \qquad (1)$$

where $x$represents the classical physiological feature vector and $| \phi(x)\rangle$denotes its quantum feature representation.

The similarity between two physiological samples is computed using the quantum kernel function

$$K(x_i, x_j) = |\langle \phi(x_i) | \phi(x_j)\rangle|^2 \qquad (2)$$

where $K(x_i, x_j)$denotes the similarity between two physiological samples in the quantum feature space.

The final health status is determined using the QSVC decision function

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \qquad (3)$$

where $\alpha_i$is the Lagrange multiplier, $y_i$is the class label, $K(x_i, x)$represents the quantum kernel, and $b$denotes the bias parameter. Fig. 3 presents the QSVC-based classification process adopted in the proposed healthcare monitoring framework**.**

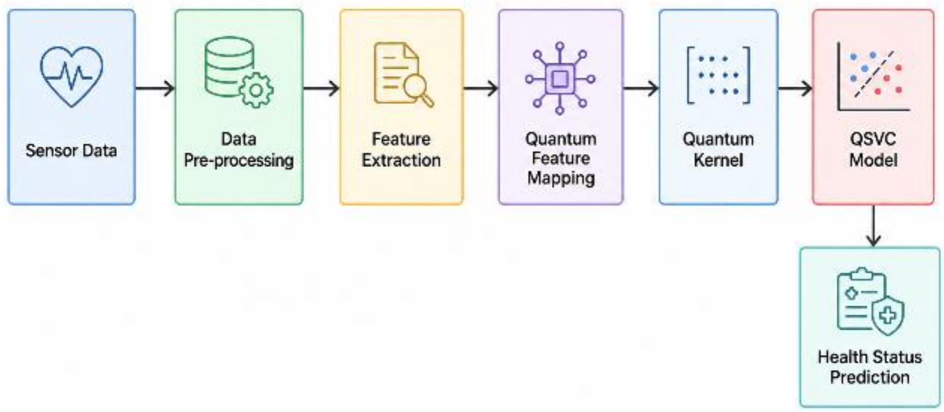

Fig. 3. QSVC Classification Process

Algorithm 1. Proposed QSVC-Based Health Status Prediction

Input: Physiological parameters (ECG, Heart Rate, Body Temperature, SpO_2)

Output: Predicted Health Status (Normal / Abnormal)

1. Initialize the wearable healthcare monitoring framework.
2. Acquire physiological parameters from the wearable biomedical sensors.
3. Collect and process the sensor readings using the Arduino Uno.
4. Transmit the processed physiological data to the cloud platform through the ESP8266 Wi-Fi module.
5. Perform data preprocessing, including validation and feature normalization.
6. Transform the preprocessed feature vectors into the quantum feature space.
7. Compute the quantum kernel matrix for feature similarity evaluation.
8. Apply the Quantum Support Vector Classifier (QSVC) to classify the physiological data.
9. Determine the patient's health status as Normal or Abnormal.
10. Display the prediction results through the
11. Flask-based web application.
12. Continue physiological monitoring until the monitoring session is terminated.
13. End the algorithm.

3.4 System Workflow

The operational workflow begins with continuous acquisition of physiological parameters using wearable biomedical sensors. The collected sensor data are processed by the Arduino Uno and transmitted to the cloud platform through the ESP8266 Wi-Fi module. After preprocessing, the QSVC model performs intelligent health status classification, and the prediction results are visualized through the Flask-based dashboard for continuous remote patient monitoring.

Fig. 4 depicts the complete workflow of the proposed AI-enabled wearable healthcare monitoring framework from physiological data acquisition to health status prediction

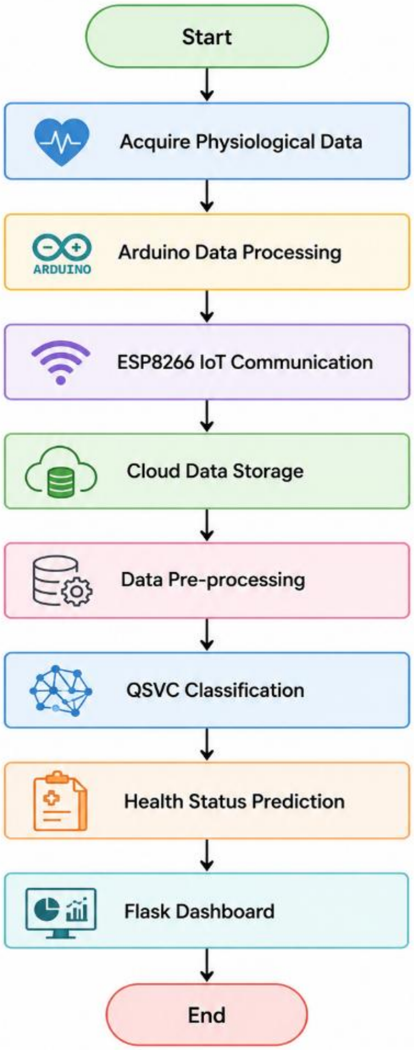

Fig. 4. Workflow of the Proposed System

4. Experimental Setup

The experimental setup was designed to evaluate the performance of the proposed AI-enabled wearable healthcare monitoring framework under real-time operating conditions. The framework integrates wearable biomedical sensors, Arduino-based data acquisition, ESP8266-enabled IoT communication, Quantum Support Vector Classifier (QSVC), and a Flask-based web application. The experimental environment includes both hardware and software components required for physiological data acquisition, intelligent classification, and health status visualization.

4.1 Hardware Configuration

The proposed healthcare monitoring system employs wearable biomedical sensors to continuously acquire physiological parameters, including ECG, heart rate, body temperature, and blood oxygen saturation (SpO_2). The acquired sensor signals are processed by the Arduino Uno and transmitted to the cloud platform using the ESP8266

Wi-Fi module. A personal computer is utilized for QSVC model implementation and dashboard deployment. Table 3 summarizes the hardware configuration adopted for the proposed framework.

Table 3. Hardware Configuration

Component	**Specification**	**Purpose**
Arduino Uno	ATmega328P	Sensor data acquisition
ESP8266	Wi-Fi Module	IoT communication
ECG Sensor	Biomedical Sensor	Cardiac activity monitoring
Heart Rate Sensor	Pulse Sensor	Heart rate measurement
Temperature Sensor	Digital Sensor	Body temperature monitoring
SpO_2 Sensor	Pulse Oximeter	Blood oxygen monitoring
Personal Computer	Intel Core i5, 8 GB RAM	QSVC execution and dashboard

4.2 Software Configuration

The proposed framework was implemented using Python-based development tools and scientific computing libraries. Arduino IDE was employed for programming the Arduino Uno, while Flask was used to develop the web-based monitoring dashboard. The Quantum Support Vector Classifier was implemented using the Qiskit framework. Additional libraries were incorporated for preprocessing, numerical computation, visualization, and model evaluation. Table 4 presents the software environment utilized during the experimental study.

Table 4. Software Configuration

Software / Library	Purpose
Python 3.x	Framework implementation
Arduino IDE	Arduino programming
Flask	Web application development
Qiskit	QSVC implementation
Scikit-learn	Data preprocessing and evaluation

NumPy	Numerical computation
Pandas	Data processing
Matplotlib	Performance visualization
Windows 11	Operating environment

4.3 Performance Evaluation Metrics

The effectiveness of the proposed Quantum Support Vector Classifier (QSVC) was assessed using standard classification metrics, namely Accuracy, Precision, Recall, and F1-Score. These evaluation measures quantify the predictive capability of the proposed framework for distinguishing between normal and abnormal physiological conditions.

The overall classification accuracy is computed as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Where TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative samples, respectively.

The precision metric is expressed as

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

where TPrepresents correctly classified fault samples and FPdenotes incorrectly predicted fault instances.

The recall measure is calculated according to

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

where FNdenotes the missed fault samples.

The harmonic relationship between precision and recall is determined using the F1-score.

$$F1 = \frac{2PR}{P + R} \quad (7)$$

where $P$and Rrepresent precision and recall, respectively.

5. Results and Discussion

The proposed AI-enabled wearable healthcare monitoring framework was evaluated to assess its classification performance and real-time monitoring capability. The experimental results validate the effectiveness of integrating IoT communication with the Quantum Support Vector Classifier (QSVC) for intelligent physiological health monitoring.

5.1 Classification Performance

The performance of the proposed QSVC model was evaluated using Accuracy, Precision, Recall, and F1-Score. Fig. 5 presents the classification performance achieved during experimentation.

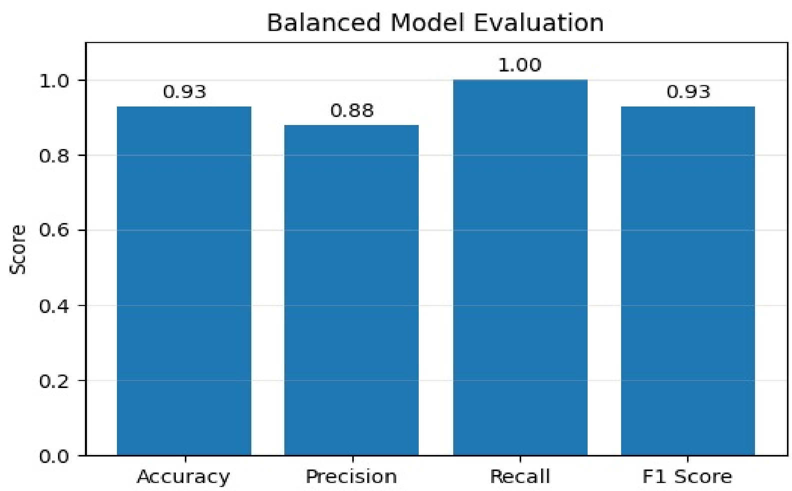

Fig. 5. Performance Evaluation

As illustrated in Fig. 5, the proposed model achieved 93% Accuracy, 88% Precision, 100% Recall, and 93% F1-Score. These results demonstrate the capability of the QSVC model to accurately classify physiological conditions while effectively identifying abnormal health cases.

5.2 Web-Based Healthcare Monitoring Interface

A Flask-based web application was developed to facilitate remote healthcare monitoring and visualization of prediction results. Fig. 6 illustrates the homepage of the proposed healthcare monitoring platform.

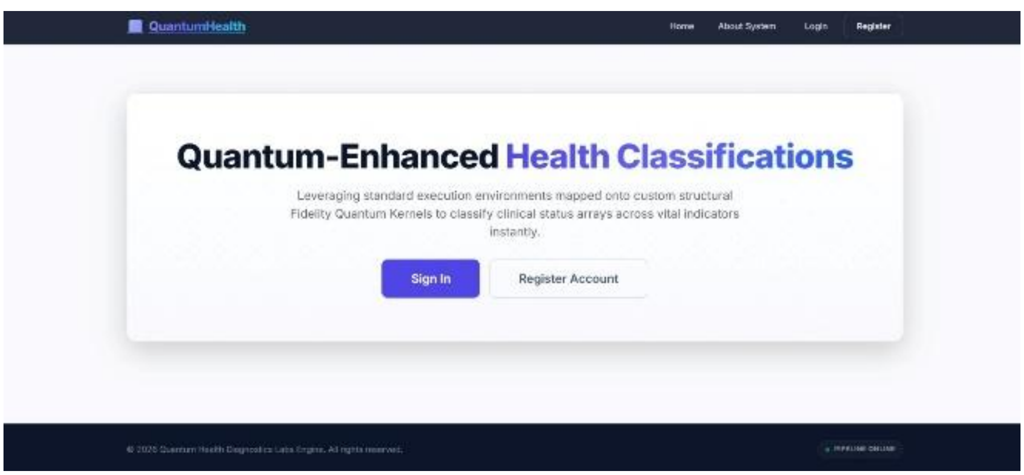

Fig. 6. Home Interface

The developed interface provides access to system features, physiological monitoring, and intelligent health prediction through an intuitive dashboard.

5.3 Health Status Prediction

The developed prediction module classifies the physiological condition as either Normal or Abnormal based on the acquired sensor measurements. Fig. 7 presents the prediction interface for a normal physiological condition.

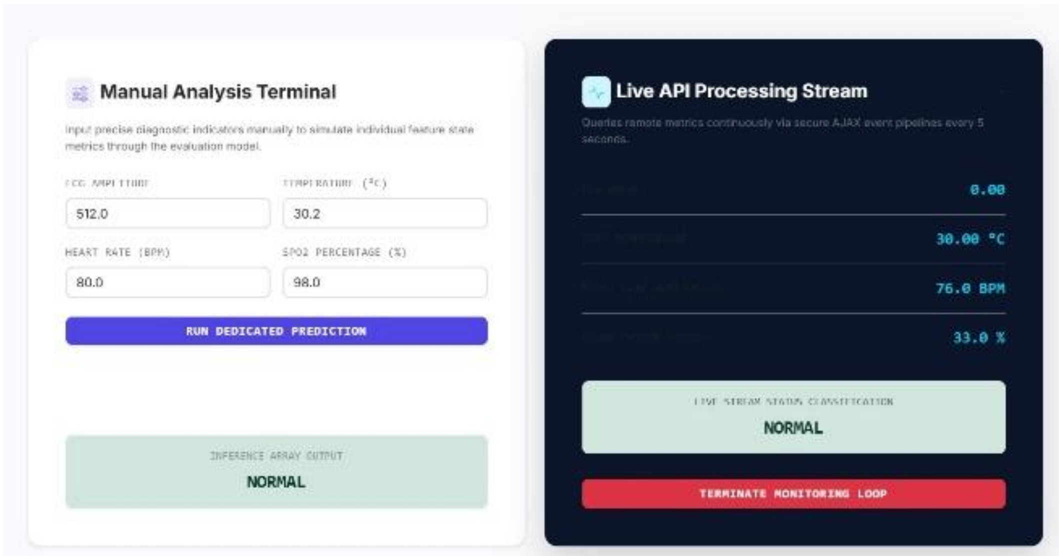

Fig. 7. Normal Health Status Prediction

The prediction result shown in Fig. 7 indicates that the acquired physiological parameters are classified as Normal by the proposed QSVC model. Fig. 8s illustrates the prediction result for an abnormal physiological condition.

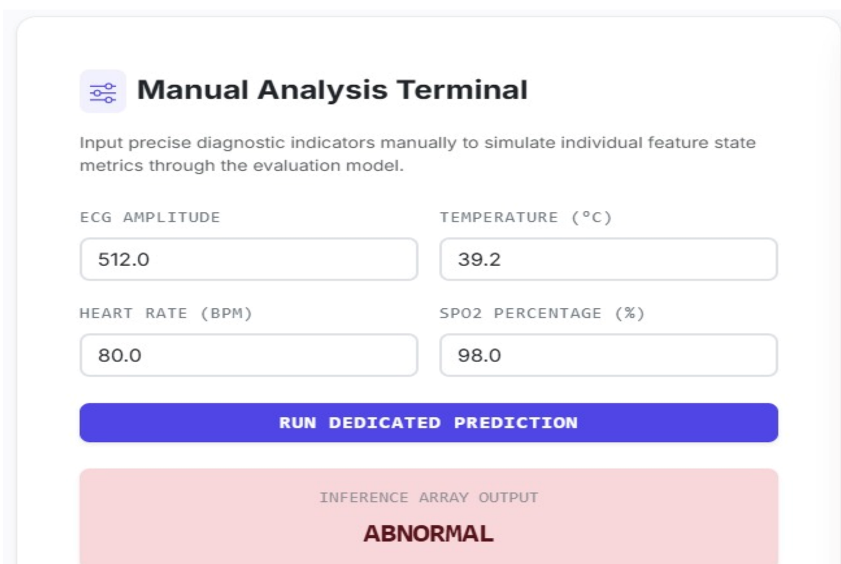

Fig. 8. Abnormal Health Status Prediction

As shown in Fig. 8, abnormal physiological measurements are successfully identified by the QSVC model, demonstrating the effectiveness of the proposed framework for intelligent health status prediction.

6. Conclusion

This paper presented an AI-enabled wearable healthcare monitoring framework that integrates wearable biomedical sensors, Arduino Uno, ESP8266-based IoT communication, and a Quantum Support Vector Classifier (QSVC) for intelligent health status prediction. The developed framework enables continuous acquisition, processing, and visualization of physiological parameters through a Flask-based web application. Experimental results demonstrate that the QSVC model effectively classifies normal and abnormal health conditions using multiple physiological measurements, supporting reliable real-time healthcare monitoring. The integration of IoT and quantum machine learning provides an efficient approach for remote patient monitoring and timely health assessment. Future work will focus on extending the framework with larger clinical datasets, additional physiological parameters, and enhanced quantum learning techniques to further improve prediction performance and practical healthcare deployment.

References

[1] H. Alemdar and C. Ersoy, "Wireless sensor networks for healthcare: A survey," Computer Networks, vol. 54, no. 15, pp. 2688–2710, Oct. 2010.

[2] S. Baker, W. Xiang, and I. Atkinson, "Internet of Things for smart healthcare: Technologies, challenges, and opportunities," IEEE Access, vol. 5, pp. 26521–26544, 2017.

[3] S. Majumder, T. Mondal, and M. J. Deen, "Wearable sensors for remote health monitoring," Sensors, vol. 17, no. 1, Art. no. 130, 2017.

[4] M. Chen, Y. Ma, Y. Li, D. Wu, Y. Zhang, and C. H. Youn, "Wearable 2.0: Enabling human-cloud integration in next generation healthcare systems," IEEE Communications Magazine, vol. 55, no. 1, pp. 54–61, Jan. 2017.

[5] A. Gatouillat, Y. Badr, B. Massot, and E. Sejdić, "Internet of Medical Things: A review of recent contributions dealing with cyber-physical systems in medicine," IEEE Internet of Things Journal, vol. 5, no. 5, pp. 3810–3822, Oct. 2018.

[6] H. Habibzadeh, K. Dinesh, O. Rajabi Shishvan, A. Boggio-Dandry, G. Sharma, and T. Soyata, "A survey of Healthcare Internet-of-Things (HIoT): A clinical perspective," IEEE Internet of Things Journal, vol. 7, no. 1, pp. 53–71, Jan. 2020.

[7] A. Esteva, A. Robicquet, B. Ramsundar, et al., "A guide to deep learning in healthcare," Nature Medicine, vol. 25, no. 1, pp. 24–29, 2019.

[8] S. D. Mamdiwar, A. R., and Z. Shakruwala, "Recent advances on IoT-assisted wearable sensor systems for healthcare monitoring," Biosensors, vol. 11, no. 10, Art. no. 372, 2021.

[9] V. Dunjko and H. J. Briegel, "Machine learning and artificial intelligence in the quantum domain," Reports on Progress in Physics, vol. 81, no. 7, Art. no. 074001, 2018.

[10] M. Schuld and F. Petruccione, Quantum Machine Learning: An Introduction. Cham, Switzerland: Springer, 2018.

[11] M. Schuld, A. Bocharov, K. Svore, and N. Wiebe, "Circuit-centric quantum classifiers," Physical Review A, vol. 101, no. 3, Art. no. 032308, 2020.

[12] M. Schuld, "Supervised quantum machine learning models are kernel methods," arXiv:2101.11020, 2021

[13] K. Bache and M. Lichman, UCI Machine Learning Repository. Irvine, CA, USA: University of California, 2013.

[14] F. Chollet, Deep Learning with Python, 2nd ed. Shelter Island, NY, USA: Manning Publications, 2021.

[15] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.

[16] M. A. Nielsen and I. L. Chuang, Quantum Computation and Quantum Information, 10th Anniversary ed. Cambridge, U.K.: Cambridge University Press, 2010

[17] IBM Quantum, "Qiskit: An open-source SDK for quantum computing," IBM, 2024.

[18] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in Proc. Int. Conf. Learning Representations (ICLR), 2015.

[19] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[20] W. McKinney, "Data structures for statistical computing in Python," in Proc. 9th Python in Science Conf. (SciPy), Austin, TX, USA, 2010, pp. 56–61.