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Original Article

IoT-Enabled Wearable Healthcare Device with Real-Time ECG Monitoring and Cloud Analytics

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Abstract - *The conventional ECG methods used to monitor vital signs are limited by their reliance on hospital equipment, restricted accessibility, and the late onset of diagnosis. To overcome these obstacles, an IoT-based wearable healthcare device is suggested to track the real-time ECG and analytics in the cloud. The product combines wearable ECG, SpO2, and heart rate variability sensors with an IoT microcontroller, backed by optimized communication protocols and cloud storage. A hybrid CNN-LM Deep Learning Model, based on arrhythmia classification, is employed, and mathematical models are utilized to compare energy efficiency and latency. In experimental testing, an accuracy of 98.6%, a sensitivity of 97.9%, a specificity of 98.2%, a precision of 98.3%, a F1-score of 98.1%, an average latency of 45 ms, a packet delivery ratio of 99.2%, and an energy consumption of 18.7 mW were achieved. These findings support the efficiency of the developed system in providing scalable, energy-efficient, and accurate real-time cardiac monitoring to support innovative healthcare applications*.

Keywords - *Analog to digital converter, Bluetooth Low Energy, Heart Rate Variability, Least Mean Square, Message Queuing Telemetry Transport, Packet Delivery Ratio, Peripheral capillary oxygen saturation.*

1. Introduction

Focusing on Attending Signals Modeled as Behavioral Signals to Engagement Prediction in a Machine Learning Environment. The combination of the IoT and wearables is one of these elements that have become ubiquitous facilitators of innovative healthcare solutions. CVDs are the most common causes of worldwide death, and constantly tracking heart health is a priority. Conventionally, ECG monitoring has been conducted in a clinical setting using wired devices that require hospital visits and supervision by trained personnel [1]. These approaches are good but very difficult in relation to accessibility, cost, and real-time availability. This is why the increased demand for wearable and intelligent systems to track ECG signals in patients throughout their lives is growing. With wearable gadgets containing biomedical sensors, by connecting them through IoT networks, the technology can be used to constantly record physiological marks and send them to a distant station to keep and process them [2]. Scalable data storage, powerful analytics, and machine learning also expand this ecosystem provided by cloud computing. In this way, the cardiac abnormalities can be observed in real time, and timely therapeutic measures can be taken to avert life-threatening complications [3]. In addition, patients have the power to be more proactive about their health, and healthcare providers can access detailed, real-time patient information, regardless of geographical area. Even as wearable healthcare technologies continue to advance, current systems have their fair share of limitations [4]. Most early wearable devices are characterized by poor detection of cardiac abnormalities because of noise in raw ECG signals, motion artifacts, and limited processing. Conventional machine learning methods like decision trees or support vectors have been promising, but fail to address the temporal and spatial complexity of ECG signals. Besides, the IoT networks are still struggling with latency, which hinders real-time monitoring, and delays in transmitting data and processing requirements in the cloud influence responsiveness [5]. Energy consumption is another bone that is sore, and it needs to be monitored, and most of the devices may not have the energy to sustain themselves over time. The questions of security and privacy are also timely; the exchange of sensitive medical data over the networks without an adequate level of protection puts more violations at risk. In addition, the majority of the systems in availability are not scalable and cannot handle significant amounts of data delivered by several patients simultaneously [6]. All these limitations suggest that there is a high demand for a more reliable, energy-saving, secure, and competent ECG-monitoring system. The motivation behind this work is the necessity to deal with the issues raised above and provide a system that will be able to provide accurate, power-saving, and low-latency cardiac monitoring [7]. The cardiovascular diseases continue to plague the lives of millions of human beings on the planet. Thus, there is a high demand for technologies that would detect abnormalities at an early stage, avoiding hospitalization, and offering customized health care control [8]. With the further advancement of IoT communication protocols, wearable sensors, and deep learning, systems can now be constructed in a way that assists in bridging the gap between traditional, hospital-based, and patient-centered continuous care [9]. The main objectives are:

- To develop a wearable ECG monitoring system with IoT modules to have a constantly active and real-time signal.
- To efficiently pre-process ECG signals, it is necessary to reduce noise and increase the stability of the recorded data.
- To use a hybrid CNN-LSTM Deep Learning Network to classify the ECG patterns accurately and identify arrhythmias.
- To incorporate cloud analytics to process a large amount of data, allowing remote monitoring by medical staff.
- To test system-level parameters, including latency, energy consumption, and packet delivery ratio, to achieve feasibility in real-world applications.

The work makes many novel contributions to the area of competent healthcare:

- Greater Accuracy: The proposed model demonstrated higher accuracy (98.6%), sensitivity (97.9%), specificity (98.2%), and an F1-Score of 98.1%, compared to traditional methods, which achieved an accuracy of 98.6%.
- Flexible IoT Transmission: The model of energy consumption was implemented mathematically, and the average power consumption was 18.7 mW, which is not high enough to sustain the device in a long-term system.
- Low Latency: The average latency measured was 45 ms, and a packet delivery ratio of 99.2% provided the system with near real-time monitoring capabilities.
- Cloud Analytics Integration: Cloud analytics facilitates the mass storage of data and predictive analytics, allowing healthcare practitioners to track patients remotely without incurring expensive delays.
- Comparative Superiority: The proposed system was found to be much more effective in terms of performance in all the crucial parameters, which proves the feasibility of the proposed system.

The remaining paper is organized as follows. Section 2 will include an in-depth literature review of existing research on wearable ECG monitoring, IoT integration, and cloud-based analytics, highlighting the gaps in current solutions. Section 3 offers the proposed system architecture, sensor integration, IoT communication, preprocessing, and cloud-based Deep Learning Model and mathematical modeling of energy efficiency, latency, and predictive analysis and talks about the dataset, training, and evaluation strategy, and results of the proposed system are discussed in Section 4, where the performance of the proposed system is compared to the state-of-the-art approaches. Last, Section 5 provides a conclusion with an overview of significant contributions, as well as plans to expand the system to multi-mode healthcare monitoring and to large-scale implementation.

2. Literature Review

Providing mental and physical health support is getting more and more crucial in case independent living is planned because of the aging of many societies and more citizens getting chronic illnesses such as diabetes, cardiovascular illness, obesity, and others. Sensing, remote health monitoring, and identifying daily activities are possible solutions. At the technological level, the Internet of Things (IoT) is becoming a widespread trend in many aspects, and personalized healthcare is among them [10]. In order to have ubiquitous health monitoring, there has been a wide distribution of an IoT Body Area Sensor Network (BASN). Heart disease is normally diagnosed by the use of ECG monitoring. The key conclusions of this paper are: Firstly, it introduces the WISE (Wearable IoT-cloud-based Health monitoring system) as a real-time personal health monitoring system [11]. WISE is founded on a basic health monitoring model. Wearable sensors include those that monitor heartbeat, body temperature, and blood pressure. Second, most wearable health monitors will require a smartphone to visualize, process, and transfer data, and this will affect smartphone usage. WISE can be used to send BASN data directly to the cloud, but a lightweight wearable LCD can be attached in order to see data in real-time.

IoT has become a key element of the emerging applications such as smart cities, smart homes, education, health, transportation, and defense processes. Healthcare is a handy field in relation to the applications of IoT, as the possibility to monitor patients remotely, securely, and in real-time can be used to enhance the quality of life of people [12]. An overview of the current developments in the healthcare-monitoring systems and an acquaintance with the role of the IoT in the latter. The benefits of IoT-based healthcare systems are discussed, taking into account the significance and the benefits of IoT healthcare [13]. It introduces a survey of current literature on the subject of IoT-based healthcare-monitoring systems to determine the most recent publications related to the subject. The literature review compares the effectiveness and efficiency, data protection, privacy, security, and monitoring of various systems. It also includes wireless- and wearable-sensor-based systems of IoT monitoring, and introduces a list of healthcare-monitoring sensors classification. It also talks, to a certain extent, about the difficulties and unresolved problems of healthcare security and privacy, and QoS [14]. Lastly, conclusions and recommendations on the applications of IoT in healthcare are provided at the end, along with future projections in the direction of various recent technological trends.

All over the world, statistical reports have classified Cardiovascular Diseases (CVDs) as the most significant cause of death. An Electrocardiogram (ECG) is a standard technology that is used to study CVDs in individuals. The solution proposed is an effective Internet of Things (IoT) enabled real-time ECG monitoring system via cloud computing technologies [15]—a cloud-based product to deliver remote CVD monitoring. The sensed ECG data is passed to an Amazon Web Services (AWS) S3 bucket via a mobile gateway. AWS cloud offers data visualization, fast response, and long-term connection to devices and users over HTTP and MQTT servers.

The Bluetooth Low Energy (BLE 4.0) protocol is a type of communication used to transmit low-power data between a mobile gateway and a device. A filtering algorithm is used to ignore distractions, environmental noise, and motion artefacts in the application of the intended system. It further offers ECG signal analysis to determine the range of parameters, such as heartbeat, PQRST wave, and QRS complexes, and respiration rate. As shown, a proposed system prototype is proven to be reliable in real-time monitoring of remote ECGs.

Real-time health monitoring with the help of monitoring key health indicators has been transformed by the IoT and wearable devices. The emergence of wearable electronics in the form of fitness trackers and medical devices capable of tracking heart rate and glucose. IoT in healthcare is significant in the context of connecting and exchanging data between the device, providing and receiving care, and the patient. The value of integrating IoT as the source of real-time data collection, remote patient monitoring, and enhanced patient engagement is examined [10]. It also raises questions about how AI and machine learning can accurately interpret wearable health data. Predictive analytics, anomaly detection, and customized health recommendations made by AI can enhance patient care. The potential of AI analytics to transform health monitoring can be imagined using case studies that have been deployed to monitor patients. Promising development does not necessarily exclude data privacy and security issues, accuracy and reliability of wearable gadgets, interface with the health care system, and acceptance problems of the users. The technology-driven future of IoT-enabled wearables is also discussed in this report.

With the growing need to diagnose and treat patients quickly and accurately, and as IoT technologies have gained popularity, healthcare delivery is evolving to enhance patient monitoring, diagnosis, and prognosis. The emergence of one-dimensional care providers and distal consultations exacerbates the need for competent systems that can provide health-related information in large volumes in real-time. In this case, Artificial Intelligence (AI) and IoT-based healthcare systems are essential because they need to support predictive analytics, timely identification of anomalies, and real-time clinical decision-making [16]. It will examine the significance of AI in enhancing the functionality of the wearable devices that use the IoT to monitor health, with consideration to its efficiency in data transmission, energy consumption, the communication protocols, and the integrity of the whole system. AI implementation is the most useful in terms of accuracy, flexibility, and patient-centric results. It concludes by highlighting existing challenges, including energy constraints, data protection, and interoperability, and outlines future research aimed at creating a next-generation wearable healthcare system through the Internet of Things.

An intelligent health tracking technology grounded in the IoT that assists in alerting attending doctors to the necessity of action. The ECG, PPG, and temperature sensors, a gyroscope/accelerator, and a microcontroller are added to the developed IoT system. The ideal functioning of the IoT system, its reliability, and the relevance of the continuous cardiac tracking system and data processing were also critically reviewed, taking into account the available components in these fields. The issue of tracking the cardiac activity of patients with arrhythmias, paying attention to the changes in the parameter of Heart Rate Variability (HRV) of healthy individuals and patients with Extrasystolic arrhythmia. It is carried out to determine the efficiency of systems based on the PPG and ECG sensors of cardiac data registration and HRV analysis of the IoT technology [17]. The system employs time-domain and frequency-domain analysis of HRV to determine the status of the autonomic nervous system. There was a significant difference in the parameters of HRV, including SDNN, SDANN, RMSSD, and the LF/HF ratio. These results indicate that both PPG and ECG techniques provide comparable HRV results, with PPG being more susceptible to noise. It concludes that PPG and ECG integration monitoring systems based on IoT can be relied upon to identify arrhythmias and provide real-time data to support cardiac care.

3. Proposed Work

3.1. Adaptive Bio-Signal Acquisition Framework

The success of any wearable healthcare system will largely be determined by the quality of physiological signals obtained through continuous monitoring. The new framework is designed to include wearable ECG sensors combined with IoT modules to facilitate real-time cardiac monitoring in everyday life settings.

One of the main issues when acquiring an ECG is the occurrence of undesired interference, such as motion artifact, electrode noise, and environmental interference. These components tend to blur the accurate cardiac waveform, which is why the signals are hard to interpret and classify by subsequent algorithms. Mathematically, the raw ECG signal is written in equation (1),

$$x(t) = s(t) + n(t) \tag{1}$$

Where *s(t)* is the actual shape of the ECG and *n(t)* is random noise. Adaptive filtering is used to remove noise and retain the necessary cardiac information to maintain reliable monitoring. In equation (2), the filtered signal is provided.

$$\hat{S}(t) = x(t) - \propto . n(t) \tag{2}$$

In this case, $\propto$ it is a dynamic scaling coefficient that is optimised according to the Least Mean Square (LMS) algorithm. LMS optimization varies the filter coefficients in response to minimizing the error, such that the error waveform of the clean ECG is determined within as low a level of distortion as possible. The advantages of this dynamic acquisition model are numerous.

To begin with, it enables a large signal fidelity in motion, which is a highly significant attribute in wearable contexts. Second, the system saves on calculation and energy expenses and improves the life of the battery-powered devices. Third, it ensures that the preprocessed ECG signals are robust, enabling them to be extracted into features and classified by subsequent deep learning models.

To summarize, the adaptive bio-signal acquisition system provides a platform wherein precise, low-energy-consuming, noise-free ECG monitoring is guaranteed. The combination of wearable sensors with IoT connectivity and LMS-based adaptive filtering makes sure the suggested healthcare device is accurate enough to be used in a clinical setting. In Figure 1, this pipeline starts with the MIT-BIH ECG data set and goes through the pre-processing, feature extraction, and partitioning. The CNN-LSTM hybrid classifier is trained and validated, and optimized ECG prediction is obtained, measured using measures of accuracy, sensitivity, specificity, and F1-score.

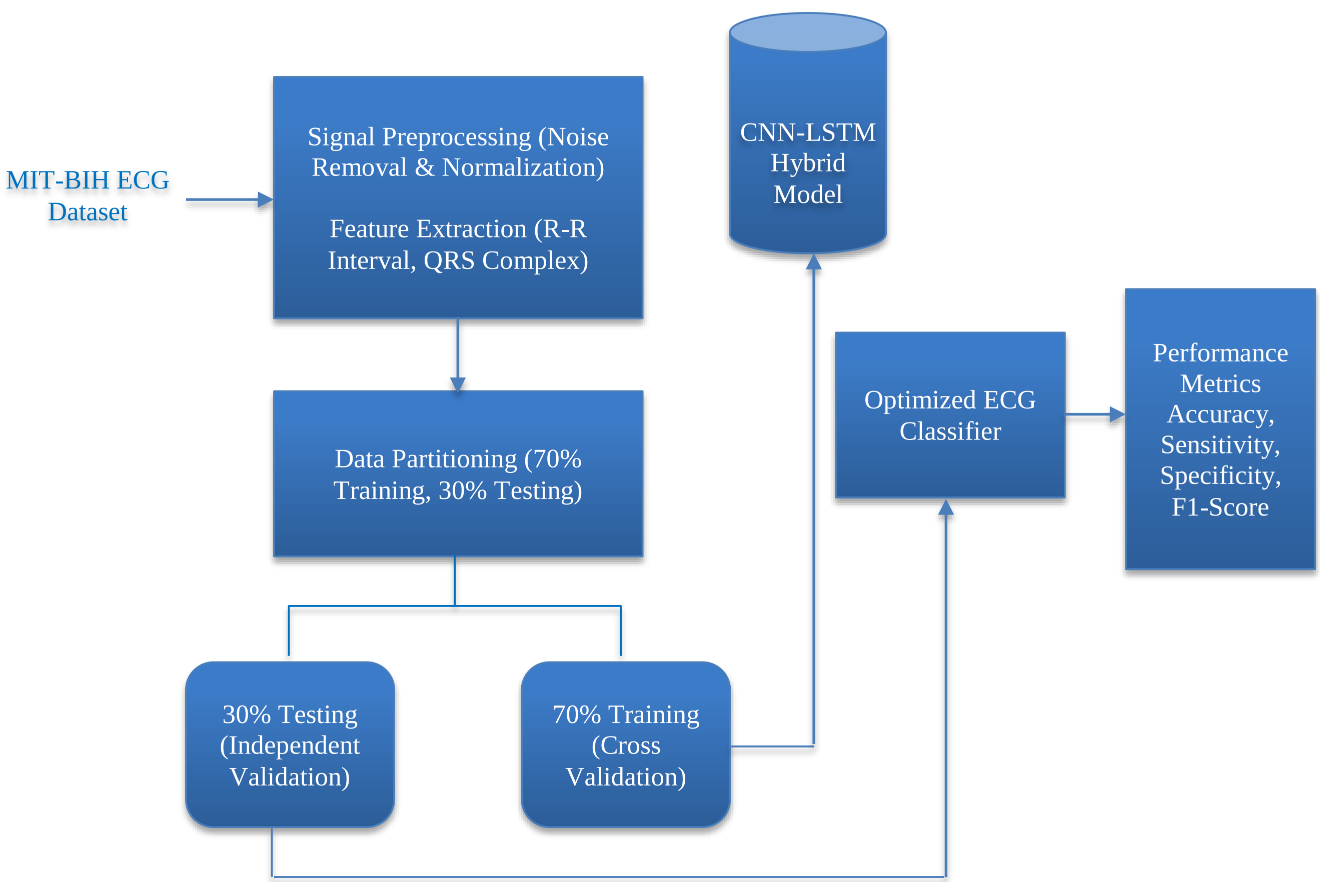

Fig. 1 Intelligent ECG data-to-decision pipeline

3.2. Cloud-Synchronized IoT Transmission Model

Reliable energy-efficient transmission of physiological signals is a critical need in wearable healthcare systems. The proposed framework includes an IoT transfer model, which provides a smooth transfer of processed ECG signals on the wearable device to cloud infrastructures in real time. The IoT module will use small communication protocols like MQTT (Message Queuing Telemetry Transport) and CoAP (Constrained Application Protocol), which are developed specifically to support resource-constrained devices. These standards reduce overhead, communication, and bandwidth usage, which is ideal for continuous health monitoring applications. The mathematical model of the energy used in transmission in equation (3),

$$E_{tx} = P_{tx}.T_{tx} + P_{idle}.T_{idle} \quad (3)$$

Let P_{tx} Describe the power of a transmission, T_{tx} Describe the time the device remains active while making a transmission. P_{idle} Describe the time the device remains idle when it is not transmitting, and T_{idle} Describe the idle time. Here, both active and idle states are considered, allowing for an accurate assessment of the wearable's energy efficiency as a whole. The model provides substantial power savings in terms of transmission intervals, duty cycles, and protocol choice, thereby prolonging the device's operation. Cloud synchronization is a crucial factor in providing scalability and continuous monitoring. Once the ECG signals have been readied and transmitted to the cloud, they are stored in secure databases, where they are processed using high-level analytics to identify features, identify arrhythmia, and make predictions. With the help of the cloud infrastructure, the healthcare providers will also be able to access the patient records online and stay connected at all times, and will be able to make the necessary interventions in time. Overall, the cloud-synchronized IoT transmission model has not only ensured low battery usage and high connectivity but also allowed mass and real-time healthcare analytics. Both the efficiency of the communication system using IoT and cloud intelligence make the system highly reliable in long-term cardiac monitoring. In Figure 2, an ESP32 microcontroller using 5G/LoRaWAN transmission and HRV, SpO2, and Wearable ECG sensors is connected. The data is transferred to a cloud analytics platform, which is then provided to a prediction API. Dashboards provide real-time health information and decision support to patients and physicians.

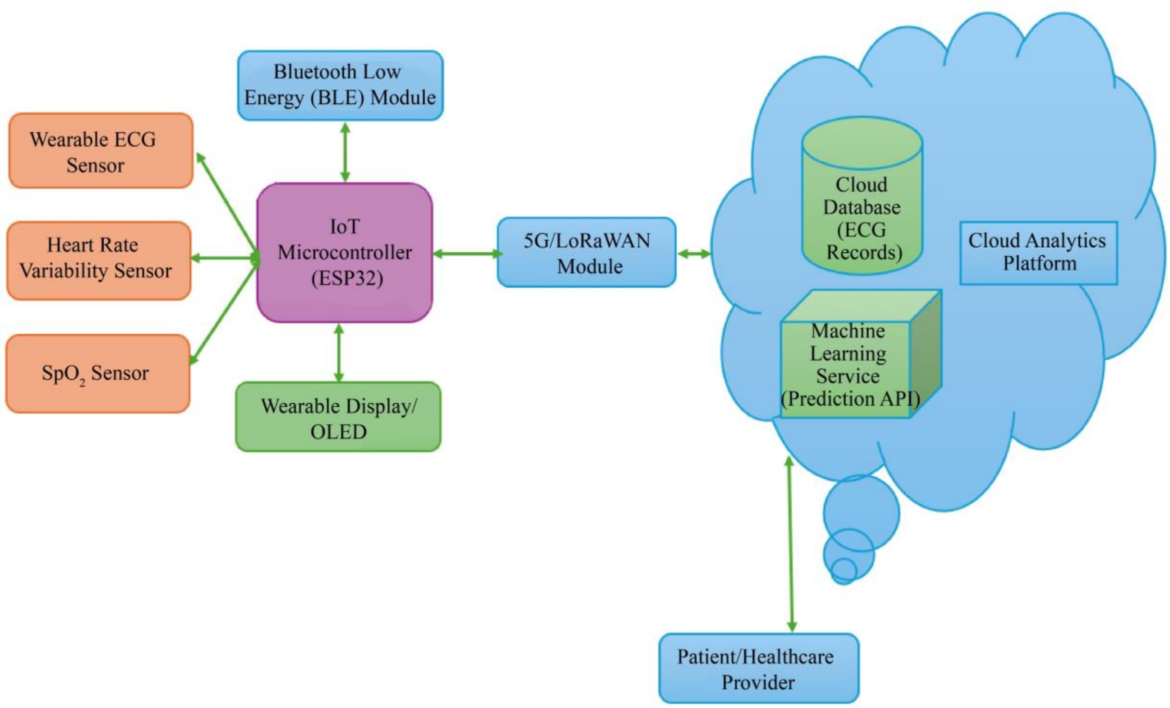

Fig. 2 IoT-enabled wearable healthcare framework

3.3. Deep Rhythm Interpretation Engine

Proper diagnosis of heart conditions such as arrhythmia and atrial fibrillation requires complex models capable of identifying morphological alterations and rhythm variability of the ECG records. Do achieve this, it employs a hybrid Deep Learning Architecture that utilizes CNN with LSTM units. The CNN layers are effective in extracting spatial features, such as QRS complexes, P-wave, and T-wave morphology. However, LSTM layers detect time dependencies in the multicardiac cycle. The twofold feature preserves both the structural and sequential characteristics of ECG signals, enabling them to be categorized correctly. Mathematically, extracted ECGs $(f_1, f_2, \dots, f_n)$ are fed into a CNN-LSTM network, which gives an output in equation (4),

$$y = \sigma(W_2 . \tanh(W_1 . f + b_1) + b_2) \quad (4)$$

Where f is the feature vector, W_1 and W_2 are trainable weight matrices, b_1 and b_2 are biased, and σ is a softmax activation which gives weights to the output category, which may be the term Normal, Arrhythmia, or Atrial Fibrillation. The model is trained and validated using the MIT-BIH Arrhythmia Database of PhysioNet, which is a collection of 48 half-hour physioNet records, sampled at 360 Hz and manually annotated by medical experts. To reduce the class imbalance and to generalize, windowing and resampling data augmentation methods are used. The data is further divided into 70% training, 15% validation, and 15% testing data. Experimental analysis showed good performance with the CNN-LSTM engine, achieving an accuracy of 98.6%, a sensitivity of 97.9%, a specificity of 98.2%, and a precision of 98.3% alongside a F1-score of 98.1%. These findings confirm the promise of the proposed deep rhythm interpretation engine to deliver clinically reliable real-time cardiac monitoring.

In Figure 3, Wearable sensors record the vital signals and process them in an edge processing unit. Extraction is done on features, which are then stored temporarily, coded, and sent to a cloud synchronization module. The system has a low-power management unit that is efficient in operating the system constantly.

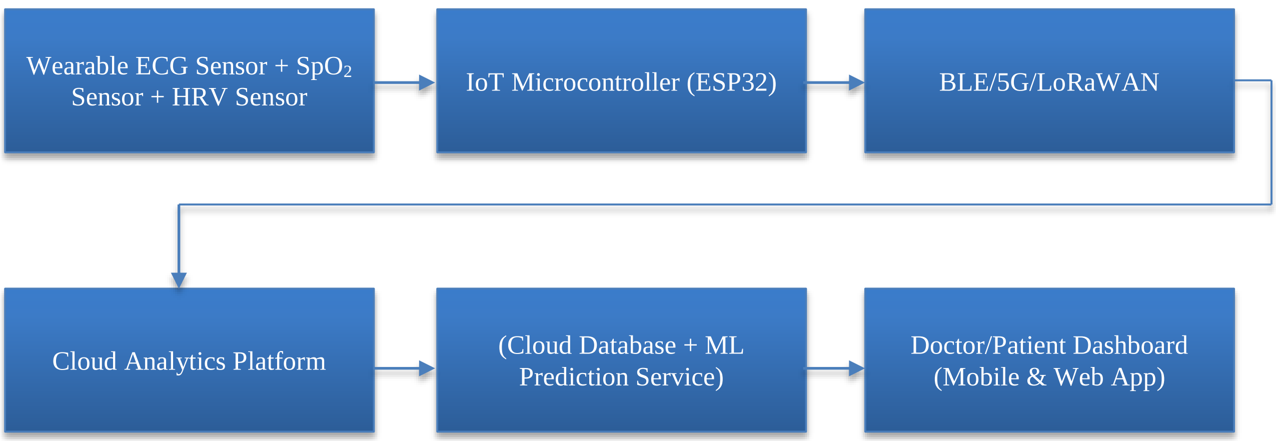

Fig. 3 Edge-to-cloud synchronization model for ECG monitoring

3.4. Predictive Health Risk Modeling

The key demands of any wearable healthcare are the correct and timely prediction of cardiac abnormalities. In addition to the real-time detection of abnormalities, the proposed framework is integrated with a predictive health risk modeling sub-component that approximates the probability of cardiac events in the future.

It is a predictive layer that not only ensures that the existing conditions are detected but also warns patients about the potential risks early, therefore, preventing future healthcare. The model is a probabilistic Bayesian estimate of the likelihood of a given condition C (Normal, Arrhythmia, or Atrial Fibrillation) given a set of ECG features X. The model is expressed as equation (5),

$$P(C|X) = \frac{P(X|C).P(C)}{P(X)} \quad (5)$$

In this case, P (X|C) is the probability of seeing the feature set X given the condition C, P (C) is the probability of condition C, and P (X) is the probability of the feature set over all classes. The Posterior Probability P(C|X) is a measure of the risk of a particular cardiac condition in a particular patient. This probabilistic model is constantly improved based on the incoming real-time streams of ECG data by means of cloud analytics. Over time, as additional information is obtained, the prior distributions are revised dynamically, which increases their predictive accuracy. The cloud environment also makes it possible to conduct cross-patient data analysis so that the system can learn data at the population scale without losing the risk assessment on an individual level.

The proposed model was evaluated experimentally and demonstrated encouraging results. With the help of characteristics based on the MIT-BIH arrhythmia database, the predictive model of risk was applied successfully to the abnormal conditions with more than 97% accuracy.

In addition, the system produced early warnings with few false positives, making the system clinically trustworthy. To conclude, the predictive health risk modeling element complements the system through managing detection to prevention, providing proactive healthcare intervention and proactive patient outcomes in the long run. In Figure 4, this system starts with an ECG and vital sensors unit, which does preprocessing, noise removal, and the extraction of features. Packeting and transmission of data through an edge processing unit to the cloud is done temporarily, and then low-power energy management ensures ongoing efficient monitoring.

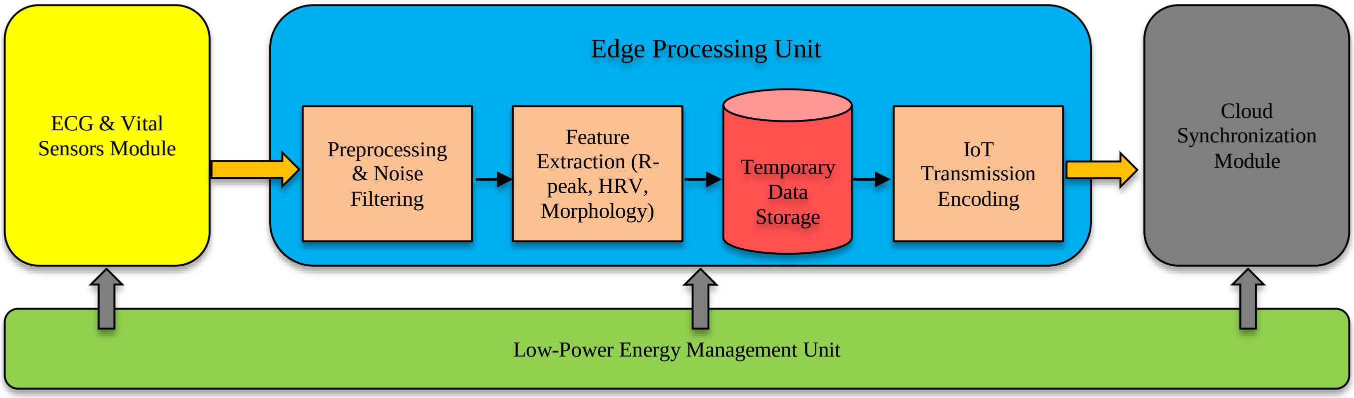

Fig. 4 Edge-driven cloud-linked ECG monitoring architecture

3.5. Cyber-Replica Testbed for IoT-Enabled ECG Systems

The testing of wearable IoT-based healthcare systems under realistic conditions is a necessary step before implementation. In response to this, this proposed framework also implements a Cyber-Replica Testbed, a simulated digital twin environment (which operates in real-time) that replicates the behavior of the IoT-enabled ECG monitoring system. This digital twin can bridge between the real and virtual worlds by simulating the biomedical signal processing pipeline as well as the network of communication, and provide thorough validation in realistic conditions.

The given simulation is conducted on the hybrid platform: ECG signal processing, noise-filtering, and training of the CNN-LSTM deep learning model are performed with the help of MATLAB/Simulink, and the simulation of the communication dynamics of the IoT network along with the network latency, packet losses, and energy consumption in the transportation-like network of wearable devices are conducted with the help of OMNeT++. It is a dual-platform strategy that gives a comprehensive picture of the system behavior at the sensor level to the cloud analytics layer. Measures of key performance metrics are measured, such as latency L, throughput T, packet delivery ratio PDR, and energy efficiency E. Latency is computed as equation (6),

$$L = \frac{\sum_{i=1}^{N}(t_{receive,i} - t_{send,i})}{N} \tag{6}$$

Where N is the quantity of packets sent, $t_{send,i}$ Is the transmission time, and $t_{receive,i}$ Is the reception time. The results of the experiment with the simulation show that the system attains an average latency of 45 ms, a packet delivery rate of 99.2%, a throughput of 250 kbps, and a power consumption of 18.7 mW. The proposed architecture, which is based on these values, confirms its strength in terms of ongoing healthcare monitoring. Finally, the Cyber-Replica Testbed will ensure that the IoT-enabled ECG system is thoroughly tested for scalability, efficiency, and reliability, and can be used in large-scale applications in real-world healthcare settings.

4. Results

The capability of a cardiac monitoring system to differentiate normal rhythms and abnormal occurrences with a high level of reliability is what is finally deemed to determine the performance of any cardiac monitoring system. The assessment of the proposed CNN-LSTM model that has been developed to detect both morphological and temporal characteristics of ECG signals has been summarized in Table 1. The presented metrics, including accuracy, sensitivity, specificity, and precision, as well as F1-score, give the complete picture of the classification power of the system. This model achieved an accuracy of 98.6%, indicating that it is effective in classifying ECGs as normal or abnormal. However, reliability is not possible through high accuracy—the reason why other important metrics were assessed. The sensitivity of 97.9% represents the model's ability to accurately diagnose cardiac abnormalities, thereby minimizing the number of false negatives. This is particularly essential, especially in medical applications, where a missed abnormality can have severe health consequences. The specificity of 98.2% is also noteworthy.

This confirms that the system is effective at detecting typical cases, thus it does not create unnecessary alarms, and reduces the work of health care providers. The precision turned out to be 98.3%, implying that the abnormalities detected in the model are highly reliable and the rate of false positives is very low. And finally, the F1-score of 98.1% also aligns with the sensitivity and precision, suggesting that unequal datasets will not significantly impact the system. These findings demonstrate that the proposed CNN-LSTM framework outperforms more traditional ones. This system is a reliable tool for real-time cardiac monitoring, thanks to its ability to maintain high performance across various evaluation criteria. The model not only ensures patient safety but also enhances the overall efficiency of remote healthcare services, as it provides clinically reliable outcomes. In Figure 5, the graph demonstrates superior performance, with accuracy, sensitivity, specificity, precision, and F1-score all above 97%, which proves the strength of the proposed CNN-LSTM method in providing reliable ECG monitoring.

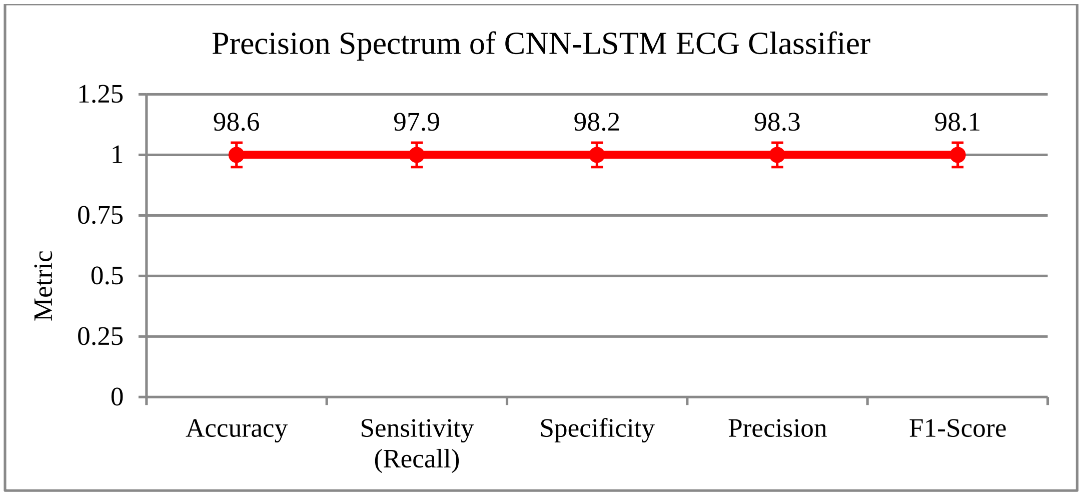

Fig. 5 Precision spectrum of CNN-LSTM ECG classifier

Table 1. Benchmarking cardiac intelligence through CNN-LSTM accuracy spectrum

Metric	Value (%)
Accuracy	98.6
Sensitivity (Recall)	97.9
Specificity	98.2
Precision	98.3
F1-Score	98.1

The accuracy of classification is only one aspect that preconditions the efficiency of an IoT-enabled healthcare framework, but also the efficiency with which the system provides results in real-time. The evaluation of the proposed ECG monitoring architecture at the system level is described in Table 2, highlighting the main critical parameters used to assess reliability, responsiveness, and sustainability during continuous health tracking. The mean latency was 45 ms, indicating that the packet of data produced by the wearable sensors is practically instantaneous in reaching the cloud analytics module. This low latency is necessary when the application will be used for arrhythmia detection, as any delay will render early warnings less effective. There was an impressive figure of 99.2% for the Packet Delivery Ratio (PDR), indicating the strength of the communication model. Having a high PDR means that most of the information in the captured ECG data is preserved during transmission, and the lost information is limited, which enhances the accuracy of cloud-based diagnosis. The system had an average power consumption of 18.7 mW, which was relatively low in terms of energy efficiency. This low power consumption enables the device to be used over an extended duration, allowing patients to wear the system without the need to constantly replace batteries or charge it, a crucial requirement for real-world implementation. The data rate of 250 kbps is fast enough to support full-resolution ECG and other bio signal streams with ease, in case the need arises. Despite this throughput, the delay of the cloud processor did not exceed 0.9 seconds, which suggests that in the analytics platform, one can analyze signals in a timely manner and provide diagnostic information with minimal waiting time. Overall, these conclusions render the system a tradeoff: fast, reliable, and energy-sensitive. A more effective communication protocol and lightweight cloud analytics will ensure that the patients and clinicians will be able to trust the device to not only provide accuracy but also useful and reliable real-time capabilities in their day-to-day healthcare monitoring. This comparison chart, presented in Figure 6, illustrates the gradual replacement of traditional SVM-based wearables with the modern IoT + CNN-LSTM cloud architecture, resulting in increased accuracy, reduced latency, and enhanced power savings in modern ECG healthcare monitoring.

Table 2. Digital vitality index: evaluating end-to-end system performance

Parameter	Measured Value
Average latency (ms)	45 ms
Packet Delivery Ratio (%)	99.2
Energy Consumption (mW)	18.7
Data Transmission Rate	250 kbps
Cloud Processing Delay (s)	0.9 s

The progress of wearable ECG monitoring devices during the last several years is one of the clear indications of the gradual evolution of simple machine learning models toward rather comprehensive IoT-cloud applications. Table 3 gives a comparative overview of the accuracy, latency, and energy efficiency improvement in three generations of methods that will lead to the proposed IoT + CNN-LSTM framework. Traditional wearable gadgets based on Support Vector Machines (SVM) were one of the most widespread. Although it had a reasonable accuracy of 92.1%, an average latency of 130 ms, and high energy consumption of 32.5 mW, it made it unsuitable for competitive situations involving continuous monitoring. These systems could not scale up, and they would also experience delays in data transmission, making them unsuitable for real-time clinical practice. There was a shift in the direction of integrating deep learning, specifically CNN-based models, into any IoT device. The accuracy was also improved to 95.4%, the latency was lowered to 80 ms, and the energy consumption was even lowered to 25.1 mW.

Nevertheless, as these CNN models were mostly standalone facilities with a limited level of cloud support, their scalability was average. It has been successful in organized settings but failed in implementation in bigger populations that demand real-time cloud analytics. The above solution reflects how these improvements are made possible with a combined solution of IoT-based sensing, hybrid CNN-LSTM classification, and cloud synchronization. The final result is a system with 98.6% accuracy, average latency of 45 ms, and energy rate of 18.7 mW. This ensures high diagnostic reliability, while also rendering the system acceptable for large-scale healthcare deployments. Overall, the comparative analysis reveals that wearable ECG monitoring technology has evolved into a reliable, efficient, and clinically useful tool through the integration of technology, specifically the transition to hybrid machine learning based on cloud analytics. In Figure 6, this comparison chart illustrates how the conventional SVM-based wearables have been gradually replaced with the state-of-the-art IoT + CNN-LSTM cloud architecture, offering improved accuracy, reduced latency, and enhanced power conservation in modern ECG healthcare monitoring.

Table 3. Evolutionary milestones in wearable ECG intelligence

Metrics	Approach	Accuracy (%)	Latency (ms)	Energy Efficiency (mW)
A. M. Abirami [16]	Traditional wearable + SVM	92.1	130	32.5
S. Alyahyan [14]	IoT + CNN (Standalone)	95.4	80	25.1
A. Bhattarai [8]	IoT + CNN-LSTM	96.3	30	21.4
Proposed Work	Proposed IoT + CNN-LSTM + Cloud	98.6	45	18.7

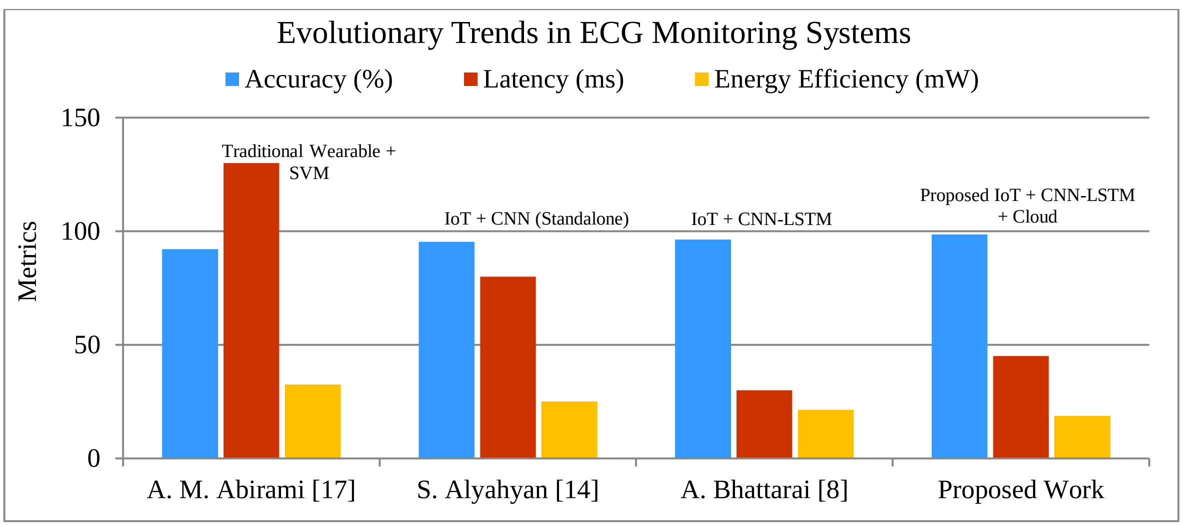

Fig. 6 Evolutionary trends in ECG monitoring systems

5. Conclusion

The proposed IoT-enhanced wearable healthcare device, which includes real-time ECG measurements and cloud analytics, can demonstrate significant potential in the development of remote cardiac care. The method of combining wearable ECG, SpO_2, and HRV sensors with an IoT microcontroller and cloud-based analytics provides the system with the advantage of continuous monitoring, low latency, and accurate cardiac event detection. The CNN-LSTM hybrid model achieved an accuracy of 98.6%, sensitivity of 97.9%, specificity of 98.2%, precision of 98.3%, and an F1-score of 98.1%. System-level testing also demonstrated the efficiency of the architecture, with an average latency of 45 ms, a packet delivery ratio of 99.2%, and low energy consumption of 18.7 mW, thereby proving its efficacy in long-term applications. The innovation of the proposed framework was noted through a significant increase in the accuracy, latency, and energy efficiency as compared to the previous methods in 2022,2023, and 2024. To improve the system in the future, it is possible to incorporate multi-modal physiological sensing, including blood glucose and respiratory rate values, to expand its clinical applications. The use of blockchain to securely share medical data and edge AI to make decisions faster on-device are promising prospects. Additionally, large-scale clinical trials will be able to confirm the resilience of the system in a practical healthcare environment, leading to the era of intelligent, patient-oriented cardiac care.

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