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# AI in Wearable Embedded Systems for Healthcare Monitoring: A Review

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**Abstract**

With an eye towards real-time health monitoring and early diagnosis, this review investigates how Artificial Intelligence (AI), Embedded Systems, and the Internet of Things (IoT) could be used in wearable healthcare technology. This study examines current developments in low-power embedded systems, edge artificial intelligence computing, sensor technologies, and IoT connections that all help to provide intelligent, energy-efficient wearable devices. Results show that although embedded microcontrollers offer continuous monitoring with low energy consumption, artificial intelligence-driven analytics increase diagnosis accuracy and enable predictive healthcare. IoT integration enables flawless data transfer for remote patient care, therefore supporting more responsive and easily available healthcare service. Important issues such data security, power constraints, ethical questions, and openness in AI decision-making still exist despite these developments. Emerging technologies such as Explainable AI (XAI), federated learning, blockchain-based security, and self-powered wearables as hopeful paths for addressing these constraints are highlighted in this study. The last point underlines how important it is to combine IoT, embedded systems, and artificial intelligence in wearable technologies to turn reactive medical practices into preventive healthcare approaches. Future studies should concentrate on developing trust, increasing openness, and boosting energy efficiency in AI-driven healthcare wearables if we are to guarantee effective deployment and general acceptance.

Keywords: Wearable Healthcare Technology, Embedded Systems, Artificial Intelligence, Remote patient monitoring, Real-Time Data Transmission, Internet of Things

## 1. Introduction

Various industries now rely on embedded systems; one of the most important fields is healthcare. The necessity of constant and real-time health monitoring technologies has been underlined by the growing frequency of chronic medical conditions like cardiovascular diseases, diabetes, and respiratory disorders [1]. Conventional healthcare approaches, which mostly rely on regular medical check-ups, could not always identify early warning signals of important health disorders, therefore postponing diagnosis and treatments. Wearable devices are one of the most important IoT technologies in the present era [2]. Wearable devices are at the centre of every conversation in IoT-related healthcare systems, as they have the potential to bring about a major transformation. They are also seen to be the ideal strategy for monitoring, tracking, and detecting chronic and viral illnesses in the healthcare sector. Wearable devices, which are considered an essential aspect of the IoTs, let patients get proper medical care at the right moment [3]. The impact of Collaborating Artificial Intelligence (AI) and embedded systems of proactive and personalized healthcare is becoming reality [4]. Wearable technology with smart sensors may constantly gather, examine, and transmit physiological data to medical professionals, thereby facilitating real-time monitoring, early disease identification, and fast medical action.

### 1.1 Background and motivation

Integrating AI into embedded system devices is transforming the health industry. With an increase in chronic illnesses like diabetes and heart disease, early detection and remote patient monitoring are more important now than ever [5]. One of the problems associated with traditional medicine methods is their model based on timely checkups, which does not cater to the proactive diagnosis of diseases and leads to delays in identification and treatment [6]. Head-mounted displays that can track physiological and biochemical variables non-invasively in real-time have shown promise in overcoming this challenge, which also makes them wearable health technologies [7]. These developments are an important leap forward in more affordable healthcare services, improving patient outcomes, and enabling a more advanced approach to treatment for public health. The use of AI-powered biosensor wearable devices produce the possibility of remote health monitoring and early intervention easier. Real-time data considerably improve diagnostic accuracy and enable timely medical action, enhancing patients' life quality and standard [8], [9].

Recent research investigations have shown how well wearable sensor systems combined with artificial intelligence may maximize data processing and improve diagnosis accuracy. Particularly in real-time health monitoring [10], triboelectric nanogenerator (TENG)-based sensors have attracted interest for their self-powered sensing capabilities. Furthermore, greatly enhancing the accessibility and effectiveness of wearable healthcare systems are the spread of cloud-based platforms and the IoT. These technologies enable healthcare practitioners to make data-driven choices in real time by means of flawless data transfer, storage, and analysis; therefore, the expanding older population and the need for reasonably priced, continuous monitoring solutions push the development of AI-powered wearable healthcare systems more and more [11]. The worldwide frequency of hearing loss and its effects on cognitive and linguistic development highlight the necessity of creative wearable technology powered by artificial intelligence [12]. Likewise, disorders like Parkinson's disease show how urgently smart healthcare systems using wearable sensors and artificial intelligence for individualized treatment and disease management are needed [5].

The demand for affordable, continuous monitoring solutions is rising as healthcare providers all over deal with budgetary and operational loads. Wearable ECG monitoring devices provide a quick approach for cardiovascular health evaluation and are ideas put out by [13]. Moreover, studies on wearable sensor-based embedded systems in health monitoring and emergency response have shown their importance, especially for vulnerable groups, including the elderly and severely sick patients [14]. By lowering reliance on costly hospital resources and hence boosting early illness diagnosis and intervention tactics, AI-powered wearable healthcare systems have the potential to transform patient monitoring [15]. The growing demand for non-invasive monitoring solutions has hastened the use of artificial intelligence in wearable healthcare devices, therefore greatly improving patient comfort and real-time illness identification. These developments support prompt medical treatments and enhanced healthcare accessibility, as highlighted in [16]. Wearable health monitoring technologies, powered by artificial intelligence-driven embedded systems, are set to completely change the field of patient care and provide proactive, individualized, and always-changing healthcare. AI and Machine Learning (ML) have transformed cardiovascular medicine, improved patient care, and streamlined medical procedures [17]. These technologies reduce the workload for medical practitioners by using advanced algorithms, therefore allowing more accurate diagnosis and effective treatment planning. Identifying risk factors, assessing health trends, and spotting acute events—all of which depend on AI-driven prediction models—ensure prompt treatments and enhanced patient outcomes by means of which timely interventions are guaranteed [18]. Moreover, the combination of artificial intelligence with wearable healthcare technologies has revolutionized the treatment of chronic diseases by providing remote monitoring solutions that close healthcare accessibility gaps and enable people to actively regulate their well-being [19]. As artificial intelligence develops, its ability to maximize tailored medication, improve decision-making, and transform patient care stays unbounded, thereby bringing in a new age of intelligent, data-driven healthcare.

### 1.2 Scope and objectives

This comprehensive survey explores recent advancements in AI-powered wearable sensor technologies for real-time health monitoring. The study systematically reviews state-of-the-art developments, emerging trends, and key challenges in integrating AI, ML, and IoT with wearable health monitoring systems. The scope encompasses wearable sensor technology, artificial intelligence integration, IoT and cloud connectivity, healthcare applications, challenges and limitations, and ethical and security considerations. This survey does not focus on the fabrication of new wearable sensors but rather synthesizes knowledge from existing research to provide a structured understanding of the field.

This survey aims to:

- To provide a review of AI-powered wearable sensor technologies.
- To analyse the impact of AI in enhancing health monitoring systems.
- To compare different AI and ML techniques used in wearable health monitoring.
- To examine the role of IoT in enabling real-time health monitoring.
- To identify key challenges and future research directions.

By achieving these objectives, this survey aims to provide a comprehensive reference for researchers, engineers, and healthcare professionals interested in the intersection of AI, wearable technology, and health monitoring.

### 1.3 Organization of the Paper

The remainder of this paper is as follows: Section **2** provides an overview of wearable embedded systems in healthcare, covering key components, advancements, and power management. Section **3** discusses AI's role in wearable healthcare, including data processing and key AI technologies. Section **4** explores AI applications in disease prediction, continuous monitoring, rehabilitation, and personalized medicine. Section **5** highlights challenges like data privacy, hardware constraints, model reliability, and ethical issues. Section **6** describes a comparative analysis of existing wearable solutions for the health sector. Section **7** outlines future research directions, including explainable AI, energy-efficient models, and predictive analytics. Finally, Section **8** concludes the survey with key insights and final remarks.

## 2. Overview of Wearable Embedded Systems in Healthcare

### 2.1 Definition and key components

#### 2.1.1 Definition

Wearable embedded systems in healthcare refer to minimized, intelligent electronic devices integrated into wearable accessories as shown in Figure 1 (such as smartwatches, patches, or smart textiles) that continuously monitor physiological parameters[2], [20]. These systems are combined with sensors, microcontrollers, and communication modules to track, process, and transmit health-related data in real time, enabling early diagnosis, disease management, and overall well-being improvement [10]. With the help of wireless systems, these wearable smart sensors can be personalized and be accessible to patients anywhere and anytime [21].

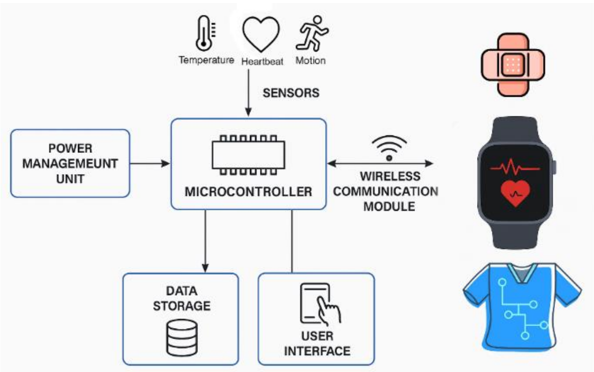


**Fig. 1.** Architecture of the Wearable Embedded System in Healthcare

#### 2.1.2 Key components

Wearable embedded devices consist of several essential components that work together to monitor and process physiological data effectively and efficiently.

**Sensors**

Wearable sensors for monitoring health can be classified into physical sensors for measuring physiological signals, chemical sensors, and biosensors for measuring chemical signals [21], [22]. For example, physical sensors can detect small-scale pressures and motions such as subtle touch, heart pulse, and motions [23]. Biosensors are sensing for enzymes, blood, urine, sweat, etc. [24]. These biosensors are called body fluid analyzers [25]. By using a combination of biosensors and physical sensors, heart rate, blood pressure, body temperature, oxygen saturation ($SpO_2$), glucose levels, and electrocardiogram (ECG) [11], [13], [26], [27], [28].

**Microcontrollers (MCUs)**

Microcontrollers (MCUs) and microprocessors (MPUs) serve as the core processing units in wearable healthcare systems, handling sensor data, executing embedded algorithms, and ensuring efficient system operation. Microcontrollers are typically used in low-power, compact devices due to their memory and I/O ports, making them the best solution for continuous health monitoring applications [29]. For example, the Cortex-M series and the Nordic nRF52840 are optimized for wearable technology with low power consumption [28]. Also, the Texas Instruments MSP430 microcontroller is commonly used in these types of ultra-low-power embedded devices [30]. Healthcare wearables require real-time analysis of physiological and chemical data. For that, edge computing-enabled MCUs, such as STMicroelectronics STM32, allow localized AI processing, reducing latency and dependence on cloud computing [31].

**Wireless communication modules**

Enables seamless data transmission between sensors and smart devices, as well as the cloud platforms. It's called the Internet of Things in general. These modules facilitate real-time monitoring, remote diagnostics, and integration with IoT-based healthcare wearable devices. Bluetooth Low Energy (BLE), Wi-Fi, Zigbee, LoRa, and 5G Cellular are the most commonly used technologies in IoT [32]. BLE is a widely used technology because it offers low power consumption and is compatible with most smartphones and devices. [33].

**Data storage & processing**

Data storage and processing are critical components in wearable healthcare systems, ensuring real-time health monitoring, efficient data management, and AI-driven analytics. Wearable devices collect vast amounts of physiological data (e.g., heart rate, ECG, $SpO_2$) [11], [13], [28] and either store it locally or transmit it to cloud servers for further processing. There are several methods to store data, such as local storage (on-device)—data stored in internal memory (Flash, SD card) before being processed—and edge computing, which unifies resources that are close to the user in geographical distance or network distance to provide computing, storage, and network for application service [34]. Fog computing is based on providing data processing capabilities and storage locally to fog devices instead of sending them to the cloud. Cloud computing transfers all data to the cloud computing centre through the network and solves the storage problems in a centralized way [34].

**User interface**

User interface is the most crucial component in wearable devices. It can be a smartphone application, website, or software application; also, it can be a display attached to the wearable device. The objective of the user interface is to provide real-time alerts and data visualization for users and healthcare providers [35].

### 2.2 Evolution and technological advancements

The development of wearable healthcare technology started through wireless communication system integration with sensor networks, which established real-time health monitoring capabilities. Mobile communication together with Bluetooth technology developed in the early stages for data transfer, which then triggered the emergence of AI analytics in wearable healthcare [8]. The advancement of wearable ECG monitors became possible as mobile Internet and wireless sensor networks developed alongside each other [13].

Wearable healthcare received significant expansion in artificial intelligence functionality during successive years because ML techniques started enabling predictive diagnostics and personalized medicine [19]. The application of AI-driven processes to wearable ECG monitoring systems delivered boosted accuracy together with enhanced efficiency and thus improved real-time cardiac health tracking reliability [15]. Non-invasive AI-powered monitoring systems have advanced as the leading technology innovation because they maintain high diagnostic accuracy without causing patient discomfort [36].

Over the past few years, sensor technology has experienced remarkable advancement alongside these other developments. FTES sensors (triboelectric sensors) represent an exceptional advancement that provides sensitive measurements with efficient power usage and complete compatibility with AI-based healthcare systems [5]. TENG stands out because it enables electricity generation from mechanical energy to operate as both a power source and a self-powered sensor [37].

AI-powered practices together with big data and sensor technology systems now allow for advanced real-time healthcare observation. The combination of AI analysis with big data has improved diagnosis precision, thus enabling prompt medical interventions according to [38]. Patient monitoring periods expanded through low-power AI-assisted wearable devices, which diminished the need for hospital visits and medical interventions [28]. Modern wearable healthcare devices keep advancing toward new limits for simultaneous monitoring and predictive conditions and premature disease recognition. [28]. The combination of wireless sensors, sensor networks, and artificial intelligence research has built a cross-disciplinary concept of ambient intelligence, addressing modern healthcare challenges through intelligent, interconnected monitoring solutions [39].

### 2.3 Power management and energy efficiency

Wearable healthcare devices require portable power systems because energy efficiency stands as an essential design factor. The sensors inside wearable medical devices need to function indefinitely since their power consumption needs optimization to meet operational requirements. [8] revealed that battery-powered prototype devices operated continually for 9 hours from a 9.6V power source, according to their research. The urgent requirement demands new methods to prolong battery life while improving the usability of devices used in practical applications.

The energy harvesting field now offers sustainable solutions through TENG technology, which researchers [5] have studied. The self-powered system transforms mechanical energy into electric power to maintain continuous health monitoring operation. TENG technology cuts down dependence on conventional batteries, thus delivering a sustainable system for managing wearable device power that provides long operational times with low energy loss. AI models need optimization for embedded systems power consumption to enable effective wearable healthcare technology. The importance of developing energy-efficient artificial intelligence algorithms for prolonging battery life during real-time health monitoring forms the core of the research of [15] and [27]. Devices that implement optimized AI architecture achieve more efficient data processing and minimize power usage because they reduce computational overhead. The performance-efficiency ratio must be optimal to succeed in extended wearable healthcare implementation.

Edge computing technology helps wearable systems operate more efficiently when it comes to power management. Devices conserve power along with lowering their data transmission overhead by conducting machine learning inference at the local device level according to [19]. Energy-efficient processing methods can be achieved through IoMT-edge computing, according to [27], when using TinyML. The approaches implemented at specific locations enable faster decision-making without compromising battery longevity, which makes real-time health checks possible. Devices must be designed efficiently, and communication systems need implementation of optimized protocols to minimize power consumption. The implementation of ZigBee communication and data compression techniques within an ECG monitoring system helped extend its battery life to exceed 160 hours, according to [40].

Additional power savings occur through the removal of unneeded circuits, including the DRL circuit, which maintains signal quality. New innovations enable the development of efficient wearable healthcare platforms that operate for longer durations. The combination of wireless communication systems enables a balance between energy conservation and efficiency of data transmission speed. The MEDIC system developed by [41] implements Bluetooth WBAN technology for sensor connectivity that preserves system power consumption. Wearable devices use low-power wireless protocols to establish uninterrupted connectivity and increase battery duration, thus providing better reliability for extended health monitoring operations.
Wearable healthcare innovation depends on uniting AI-driven power-saving models with purposeful hardware engineering and green energy technology solutions. According to [36] and [28], the optimization of power systems in AI-powered wearables serves to improve device utility and user satisfaction. The future of wearable healthcare monitoring stands to achieve record-breaking

efficiency along with sustainability and practical operation because of integrated advanced energy-efficient systems.

## 3. Role of AI in Wearable Healthcare Systems

### 3.1 AI-powered data processing in wearables

Future technology will allow wearable devices to foresee health risks along with pre-detecting anomalies early and react immediately to emergency medical conditions. The recent AI-driven advancements start to turn this futuristic healthcare scenario into reality. Machine intelligence enabled by deep learning can interpret biosignals, while Edge AI provides instant decisions through wearable technology, which transforms health monitoring systems.
Deep learning models serve as the fundamental force behind this ongoing transformation of clinical care operations. [5] established how a CNN-BiLSTM-Attention model hybrid system enhances posture recognition together with identity verification processes for obtaining precise real-time results. The research paper by [36] explains how CNNs lead to improved bio signal processing, which results in immediate physiological data interpretation. The analysis capabilities of AI for ECG remain undiscovered despite [13] preliminary findings about AI detection. Current research by [42] shows Transformer models can produce state-of-the-art results in ECG classification, thus making wearable devices more dependable than ever.

The other two essential elements, together with accuracy, contribute to the solution: speed and operational efficiency. Edge AI introduces machine learning near the user, as explained by [19], to reduce wait times and power diagnostics on handheld systems. [17] demonstrate Edge AI's ability to detect anomalies in real-time through their work, which lets healthcare interventions happen instantly in wearable devices. The MEDIC system shows this approach according to [41] through its integrated embedded inference. An engine that autonomously processes sensor data to generate on-the-spot healthcare decisions.

Wearable technology evolves into strong medical tools that detect illness risks through continuous data streams. Deep learning models strengthen wearable technology identification skills for diseases so they can serve as critical tools for disease prevention, according to [38]. The combination of artificial intelligence analytics in wearables shortens the response time to handle severe conditions such as sepsis, according to research by [28]. According to [39], artificial intelligence systems have the immediate ability to detect abnormal health patterns, which leads to life-saving opportunities for timely interventions.

The application AI in wearables serves to analyze complex sensor data as it is collected in real time. The analysis of prolonged health records through deep learning approaches provides vital information from extensive streams, according to [43]. The researchers [44] prove that AI classification systems boost data handling operations through lower cost transmission and superior system performance. The study by [45] proves that AI processes sensor data within 300 milliseconds, thus enabling immediate healthcare analysis.

In addition to personal gadgets, AI's impact encompasses cloud-based wearable healthcare solutions. [46] introduces the WISE framework as a machine learning platform that processes sensor data stored in the cloud so that distant health monitoring becomes practical on a large-scale degree. [12] prove that AI improvements result in enhanced performance speed and measurement clarity, thus enabling user-based smart health tracking worldwide. Artificial intelligence transforms wearable healthcare through its shift from basic observation to preventative actions, including automatic cognitive illness detection and fast anomaly detection alerts. Deep learning in combination with Edge AI as well as cloud intelligence helps wearables evolve to become life-saving devices that enable a smarter, healthier future, which includes real-time active protection of health.

### 3.2 Key AI technologies in wearable health monitoring

Wearable health monitoring systems have significantly evolved with the integration of AI technologies, enhancing their predictive accuracy and real-time diagnostic capabilities. Various ML and deep learning (DL) techniques are applied to process physiological data, recognize patterns, and generate reliable health insights. Key AI methods include classical ML approaches such as support vector machines (SVMs) and decision trees, advanced deep learning architectures like convolutional neural networks

**Table 1**
Key AI Technologies in Wearable Health Monitoring

| Category | Techniques | Applications | References |
|---|---|---|---|
| Machine Learning | Logistic Regression, SVM, KNN | Heart disease diagnosis, real-time data processing | [9], [10],[31], [46], [47], [48], [50] |
| Deep Learning | CNN, RNN | Pattern recognition, chronic disease monitoring | [31], [47], [48],[49] |
| Distributed Learning | Federated Learning | Privacy-preserving AI training | [17], [31], [48] |
| Predictive Analytics | Time-Series Forecasting | Advancements in wearable monitoring systems | [49], [50] |

(CNNs) and recurrent neural networks (RNNs), and novel techniques such as federated learning for privacy-preserving AI model training. Table 1 shows a summary of the AI technologies employed in wearable health monitoring, as highlighted in recent research.

## 4. Applications of AI in Wearable Healthcare Monitoring

The use of AI-driven wearable devices has risen for detecting diseases before their onset and making diagnoses in the initial stages. AI algorithms prove essential for detecting patients who will show positive responses to cardiac resynchronization therapy (CRT) and forecasting right ventricular (RV) failure among individuals receiving left ventricular assist device (LVAD) implants [53]. Rehabilitation wearables empowered by AI provide two essential solutions: the monitoring of gait patterns for multiple sclerosis patients and the support of visually impaired mobility needs, which enables stronger assisted living possibilities [54]. The HTSMNN AI model has shown excellent results for predicting Parkinson's disease, while deep learning systems prove effective in measuring anxiety [54].

The integration of wearables with AI has produced substantial changes in both preventive medical care and continuous disease management. Posture correction feedback in sports rehabilitation receives immediate feedback from AI-driven systems to enhance assisted living, which also supports better recovery monitoring. These

tracking systems monitor chronic disease parameters in real-time to deliver healthcare that delivers personalized interventions. Research shows that artificial neural networks powered by AI reach a 93.8% accuracy rate for managing chronic obstructive pulmonary disease (COPD) according to [49].

The combination of AI via wearable systems allows for the real-time acquisition and forwarding of heartbeat and temperature vital signs to hospital databases alongside mobile devices [8]. The predictive analytics feature in wearable AI technology enables the detection of dangerous medical situations ahead of time, which improves healthcare emergency readiness [28]. AI-powered human activity recognition (HAR) in wearables facilitates early detection of movement disorders, enabling timely medical interventions [9].

Wearables that incorporate advanced AI models are making substantial progress in the areas of healthcare delivery and disease diagnosis. A hybrid CNN-BiLSTM-Attention model has been shown to be highly accurate in posture recognition, a critical component of real-time health monitoring [5]. In the same vein, an Internet of Medical Things (IoMT) system that was created for Parkinson's Disease patients incorporates AI-powered feedback mechanisms, which enables continuous health monitoring and personalized care [5]. The detection of cardiovascular anomalies has been further facilitated by AI-enhanced predictive models, which have ensured that medical interventions are conducted in a timely manner [44].

Smart sensor technology, including TENGs, has been introduced by recent advancements in AI-enhanced wearables. TENGs are capable of capturing physiological signals, such as respiration, to facilitate early disease diagnosis [37]. Real-time physiological data is provided by TENG-based continuous monitoring platforms, which serve as a solid foundation for AI-driven analytics. The WISE system, which employs artificial intelligence to forecast cardiac disease based on data from ubiquitous sensors, serves as an illustration of the potential for AI models to be further refined to enable more precise predictive diagnostics [46].

AI-driven technologies are at the vanguard of healthcare innovation, revolutionizing the detection, monitoring, and management of diseases. AI-powered wearable technology enhances preventive medicine and improves patient outcomes by incorporating real-time monitoring, predictive analytics, and personalized intervention strategies. AI in ubiquitous healthcare monitoring anticipates a future of proactive, data-driven healthcare solutions as advancements persist [36], [39].

## 5. Challenges and Limitations

### 5.1 Data privacy and security concerns

Wearable healthcare systems under AI control face key challenges regarding data security and privacy because they consistently collect and handle personal health information, which needs secure transmission. The prevention of cyber threats along with misuse depends on robust encryption combined with secure transmission protocols [53]. [55] and [48] state that these issues function as fundamental obstacles to AI implementation in healthcare when regarding wearables that share real-time patient information. [54] specifies how privacy problems among elderly adults create barriers to mass adoption, so stronger security systems must be implemented.

Within wearable devices, Bluetooth offers encryption and authentication services, which serve as basic safeguards for data transfer [8]. More security methods need implementation above the baseline protection. The deployment of artificial intelligence security frameworks protects patient data privacy through advanced encryption techniques, according to [39]. Device-based AI processing protects patients by reducing the vulnerabilities of cloud storage transmission systems, which increases information confidentiality [44]. Secure Shell (SSH) establishes encrypted transmission while requiring additional security protocols because it consumes substantial resources [41]. User trust, in addition to broad market adoption, fundamentally depends on strict regulatory compliance [56].

The solution of federated learning has become a major approach for protecting privacy in artificial intelligence applications used for wearable healthcare monitoring [42]. The data-processing method of federated learning combined with aggregated model updates serves to minimize potential dangers that centralized storage methods would create. Differential privacy mechanisms upgrade system security through data-noise addition, which protects confidentiality but maintains useful AI analytical results [17].

The secure blockchain system protects wearable health data. [45] and [49] advocate for blockchain as a security solution for medical data due to its distributed network defense mechanisms, which prevent unauthorized modifications. Nevertheless, the necessity of ongoing progress in privacy-preserving blockchain solutions is underscored by the persistence of dangers such as 51% attacks. Robust security frameworks will be essential for ensuring regulatory compliance and user trust as AI-driven wearables become more prevalent in healthcare. Real-time predictive health monitoring, AI-driven personalized interventions, and secure data encryption will be essential in the development of wearable healthcare technologies [57]. The integration of federated learning, blockchain, and advanced encryption techniques in ubiquitous healthcare systems can effectively protect patient data, ensuring the long-term viability, privacy, and security of digital healthcare.

### 5.2 Energy efficiency and hardware constraints

The practicality of wearable healthcare systems heavily relies on achieving superior energy efficiency and hardware durability when they execute energy-intensive AI technologies. Research by [50] proves that sweat-activated batteries maintain stable performance during 600 bending cycles, thus proving their excellent durability. However, other durability concerns persist. The durability of batteries can be negatively impacted by two factors: inflation during 90,000 rolling cycles and poor performance through weakened Ag paste interconnections without underfill, according to [58].

Human movement velocity of 1 Hz stands as a barrier to electromagnetic harvester size reduction since it prevents effective powering of artificial intelligence-enabled wearable systems [59]. The rapid replacement of traditional batteries in wearable technology is needed because these batteries present environmental problems and inflexibility to the fabric [60]. The energy density constraints facing self-powered wearable equipment serve as hindrances to deploying AI healthcare monitoring solutions based on [61].

Researchers develop different new methods to handle these barriers yet do not resolve all performance issues. The 5.2 mW system reported in the [62] study incorporates solar harvesting functions yet confronts power delivery efficiency problems. Pyramid molding systems decrease TENG-powered wearable devices' sensitivity and restrict their ability to grow at a large scale [10]. The AFE for long-term ECG monitoring developed by [63] functioned at 560 nW but faced hardware deterioration from $rGO_x$ coatings because of their power efficiency versus sensor life balance issue. TENG technology received analysis by [5] to evaluate its capability of generating power for continuous patient health tracking through wearable systems. When employed in artificial intelligence processing according to [37], humidity proves to be a major obstacle that diminishes performance efficiency and reliability for triboelectric nanogenerators.

To maximize battery performance in wearables, manufacturers need to choose their hardware components efficiently. The study by [12] established the significance of ESP-8266 microcontrollers as a power-saving technology solution for healthcare equipment by increasing battery duration and operational reliability. According to [8] the wearable system reached 9 hours of continuous operation through its 9.6 V battery power, although present power solutions show their bounds.

Wearable healthcare technology faces major difficulties because of energy efficiency limitations combined with hardware-related restrictions. The next-generation wearables require work on how to resolve scaling challenges and environmental effects and material deterioration in addition to improvements in self-charging mechanisms and energy-efficient computer chips and power alternatives.

### 5.3 Accuracy and reliability of ai models

Healthcare wearable devices encounter multiple complex reliability obstacles because of their accuracy inconsistencies as well as unbalanced data and complex interpretability barriers. The Wearable 2.0 data imbalances are analyzed in [47] which shows that emotion detection has an accuracy rate of 81.28% for sadness identification. [64] show that CheXNet reached an F1 score of 0.435, better than radiologists yet its ability to process lateral views remains absent creating doubts about wearable monitoring systems reliability.

Research validation studies enable bridging gaps between wearable AI model development and practical implementation according to [65]. [66] present evidence showing that AI technologies struggle most with female patients and people who have low blood pressure, requiring more diverse training data for better model reliability. [67] proposed a CNN-LSTM hybrid approach to address noisy data in Human Activity Recognition, which resulted in a high 99.4% accuracy level for healthcare application reliability enhancement. Standard models decline 20% accuracy according to [68] when dealing with sensor disturbances and their corresponding reliability gap. The StatOpt framework developed by their team monitors reliability issues while providing 50% additional reliability performance for healthcare monitoring through theoretical certification standards.

The introduction of new techniques has not resolved the problem of inaccurate classification. A GRU model achieves 75.7% accuracy at gait pattern classification yet exhibits major misclassification errors that reach 32.7% for Class 2 and 30.8% for Class 3 according to [69]. Real-time health monitoring reliability faces difficulty because [70] detects comparable discrepancies in dermatological AI applications. Data poisoning impacts AI reliability according to [71], while Random Forest proves to be the most reliable model under such conditions, underlining the need for wearable AI systems to be robust.

**Table 2**
Comparative Analysis of AI-Powered Wearable Healthcare Systems

| Key Focus | Findings/Contributions | Dataset/Technology Used | Reference |
|---|---|---|---|
| AI-powered wearable applications in healthcare | AI enhances remote monitoring, disease prediction, and enables continuous, real-time assessment of physiological parameters. | Various AI-powered wearable devices, health monitoring devices | [40], [53], [55] |
| AI-powered seism cardiogram signals and cloud analytics | Potential for predicting HF hospitalization and improving patient outcomes using AI-based seism cardiogram signals and cloud analytics. | Seism cardiogram signals, cloud-based AI analytics | [49] |
| AI algorithms in wearable health monitoring | Deep learning models significantly outperform traditional approaches, enhancing activity recognition and healthcare monitoring. | Wearable sensor data (HAR datasets), wearable motion sensors | [44], [66] |
| Wearable sensor technologies | FTES outperforms existing sensors in sensitivity, response time, stability, and enhances sensor disturbance handling without added computational cost. | FTES vs. standard wearable sensors, StatOpt framework, HAR datasets | [5], [67] |

Beyond accuracy, interpretability remains a key challenge. [72] argue that while AI excels in diagnostic precision, the opacity of deep learning models hinders trust in wearable health monitoring. In contrast, [73] demonstrates the superior reliability of IBCN over conventional methods due to its uncertainty modelling, fostering greater confidence in AI-driven wearables. Meanwhile, [74] highlights the foundational role of wearable sensor validity and reliability, essential for ensuring AI-generated health insights remain trustworthy.

Collectively, these studies illustrate the intricate balance between accuracy, data integrity, and interpretability in wearable AI systems, underscoring the ongoing need for advancements to achieve truly reliable healthcare monitoring.

## 6. Comparative Analysis of Existing Solutions

The development of AI-powered wearable systems has led to various solutions designed for healthcare monitoring, fitness tracking, and disease prediction. These solutions leverage different machine learning models, sensor technologies, and data processing techniques to enhance accuracy and usability. However, variations in performance, reliability, and adaptability exist across different systems, necessitating a comparative analysis. This section examines existing AI-powered wearable systems, evaluates their strengths and weaknesses, and benchmarks their performance based on key metrics such as accuracy, response time, and robustness.

### 6.1 Review of current AI-powered wearable systems

The rapid advancements in AI-powered wearable devices have led to significant improvements in remote health monitoring, disease prediction, and patient care. Various studies have explored different aspects of wearable healthcare technology, including sensor performance, AI algorithm efficiency, and practical applications. The Table 2 presents a comparative analysis of existing AI-powered wearable solutions, highlighting their key focus areas, major findings, and the datasets or technologies used in their development.

## 7. Future Research Directions

### 7.1 Integration of explainable AI (XAI) in healthcare wearables

Healthcare wearables now benefit from explainable AI technology, which drives AI-based monitoring to new levels of trustworthiness as well as clinical transparency. XAI interpretation abilities are critical requirements to gain regulatory approvals and enhance user acceptance as well as meet ethical standards. ExoCOVID according to [75], serves as the fundamental achievement for trust building in explainable systems, while [53] showcases XAI as central to enhancing usability and interpretability in AI-powered wearable technology. According to [49], XAI functions as an essential tool for improving trust during healthcare applications of AI-driven wearables because of their interpretability challenges.

The inclusion of XAI within wearables creates fresh diagnostic opportunities that help ensure transparency in their operation. According to [76], the future will see AI together with XAI as it detects unrecognizable arrhythmia patterns to improve cardiac monitoring interpretability. According to [77], wearable healthcare technologies need actionable explanations running at all times to enhance user trust and system acceptance. Research conducted by [78] investigators exposed how explainable AI boosts stress detection transparency, which stands as an essential element for medical organizations to accept AI-controlled wellness tracking programs.

Scientific teams work toward extending XAI capabilities in wearables by creating new innovative methods to provide explainability alongside user trust. [45] recommend healthcare trackers should adopt SHAP and LIME frameworks because they enhance both interpretation capability and user acceptance. [79] advance Grad-CAM technology by adding new capabilities that enhance pain recognition explainability and make AI healthcare monitoring more acceptable to clinical professionals. The research of [54] shows that diagnostic transparency advances through metaverse applications of Grad-CAM and LIME, which opens opportunities for trustworthy AI healthcare solutions.

Wearable devices need XAI integration for the foreseeable future because they have advanced beyond innovation status. XAI emerges as a vital essential for future development because it will deepen the usability and trust levels in AI-driven monitoring systems, according to [54]. [42] advocates model interpretation of AI systems as a pivotal requirement for clinical approval and regulatory conformity to establish medical wearable acceptability. The core aspect of explainable AI drives the advancement of AI-driven healthcare monitoring because it delivers ethical solutions that combine intelligence with clinical reliability and transparency. XAI will shape the upcoming era of healthcare monitoring through personalized approaches while using effective methods and delivering accountable solutions by closing the bridge between AI technological advancement and medical practitioner trust.

### 7.2 AI-Driven predictive analytics for proactive healthcare

The integration of AI-driven predictive analytics in wearable healthcare devices is revolutionizing health monitoring and risk management. By leveraging machine learning, reinforcement learning, and cloud-based AI, researchers are paving the way for proactive healthcare solutions that anticipate health issues before they become critical. [47] introduces Wearable 2.0, a cloud-based learning system that proactively manages health risks, setting the stage for advanced AI-driven healthcare solutions. Similarly, [64] highlight the predictive power of CheXNet, demonstrating how AI can proactively detect pneumonia, a model that could extend to wearable monitoring systems. [52] envisions AI wearables enhancing predictive analytics, a crucial advancement in shifting healthcare from reactive to proactive care.

Expanding the capabilities of AI-powered predictive analytics, [10] develop wearable systems that detect Parkinson's disease and fall risks, showcasing their potential for broader proactive healthcare applications. [80] integrate Romance Languages and Linguistic Theory (RLLT) and Analytical Hierarchy Process (AHP) methodologies to create a predictive framework for coronary heart disease (CHD) management, providing early risk assessment and intervention strategies. [81] enhance their Multi-Criteria Decision-Making (MCDM) AHP symptom checker with fuzzy logic methods, strengthening diagnostic accuracy and early disease detection in wearable healthcare.

Innovative AI methodologies continue to drive advancements in predictive analytics for wearables. [82] explore Social Network Analysis (SNA) to develop predictive AI models, setting a foundation for community healthcare management (CHV). [66] propose reinforcement learning to strengthen predictive analytics, enhancing AI wearables' ability to anticipate and mitigate health risks. Furthermore, [72] demonstrates AI's ability to predict sepsis, a capability that could enhance early intervention in wearable healthcare systems.

Future research is essential to refine and validate AI's predictive potential in wearables. [65] calls for longitudinal studies to confirm the reliability of AI-powered predictive analytics in real-world healthcare applications. [70] emphasizes the need for AI-supported predictive tasks, enabling wearables to provide personalized early warnings for individuals at risk. Additionally, [71] explore generative neural networks for data augmentation, a breakthrough that could enhance the accuracy of predictive models in wearable healthcare. As AI-driven wearables continue to evolve, predictive analytics is becoming the cornerstone of proactive healthcare. By shifting the focus from diagnosing illnesses to preventing them, wearable AI is poised to empower individuals and healthcare professionals alike, making real-time health monitoring, early risk detection, and preventive care the new standard.

## 8. Conclusion

The combination of Artificial Intelligence, embedded systems, and the Internet of Things within wearable healthcare technology operates to revolutionize real-time health monitoring, disease prediction, and individualized treatment methods. Wearable technology with AI algorithms combines smart sensors with edge computing and IoT connectivity to provide extended health monitoring alongside early disease warning systems for doctors to perform proactive healthcare measures. These innovations drive better diagnosis results while maximizing treatment approaches and leading to improved patient care, which delivers both improved healthcare efficiency and accessibility and tailored medical solutions.

Wearable healthcare relies on embedded systems to process data in real-time with low power requirements because of microcontrollers and energy-efficient artificial intelligence models and wireless communication capabilities. These systems gain durability from IoT and cloud computing integration, which allows healthcare professionals to make decisions through data analysis and stored data communication. Wearable devices now employ predictive analytics and machine learning algorithms to spot health risks beforehand, which allows early warnings while searching for abnormalities and thus shifts medical care from standard response to active prevention.

The advancement of medical technologies continues while medical systems need improvements to secure data and become more energy-efficient and reliable and follow applicable regulations. The widespread adoption of wearable healthcare solutions depends on resolving these factors through the implementation of Explainable AI and federated learning and blockchain security and energy-efficient AI architectures. New developments in self-powered energy harvesting alongside embedded system miniaturization will boost the practicality of AI-driven wearables.

Technical developments in AI-powered wearables will target improved data transparency and safer computing and instantaneous processing to secure their use in medical care by patients and healthcare providers and institutions. Wearable healthcare devices powered by this integration of AI and embedded systems and IoT innovations are expected to transform future medicine with their data-driven smart healthcare solutions.

**Conflicts of Interest**

The author has no conflicts of interest.

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