Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 7, 2025

A REVIEW ON EDGE AI FOR LOW-LATENCY HEALTH MONITORING IN WEARABLE IOT DEVICES: CHALLENGES AND FUTURE DIRECTIONS

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DOI: https://doi.org/10.5281/zenodo.16731446

Article History
Received on 08 May 2025
Accepted on 08 June 2025
Published on 30July 2025

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Abstract

The increasingly popular concept of Edge Artificial Intelligence (Edge AI) has the potential to revolutionize health monitoring by allowing wearable devices to locally process health data on-device. This kind of approach obviates the need to transmit data to the cloud, and provides for reduced response latency, power consumption, and privacy concerns. In this review, we investigate how Edge AI is used for the real-time health monitoring with wearable IoT devices. An initial set of 42 papers was selected using title and abstract keywords matching, 21 High-quality articles were isolated for full review after using these inclusion & exclusion criteria available since 2020 to the beginning of 2025 and will concentrate on the state of the art in Edge AI for wearable health monitoring applications. Discuss an array of challenges including the power constraints and low sampling resolution of the devices used, and present future directions for advancing applications of Edge AI systems. The goal of this article is to offer a straightforward

INTRODUCTION

Wearable health gadgets are everywhere now. Everyone and their grandma's rocking a smartwatch or some kind of tracker. Honestly, it's wild how these things watch your heart rate, blood oxygen, even your ECG and glucose, all while you're just living your life. It's not just for fitness junkies, either—stuff like catching health problems early or alerting someone if you're about to pass out? Kind a game-changing.

But here's the kicker: most of these wearables used to just dump all their data into the cloud. That's cool for storage and all, but it's got some serious downsides. Leggy responses, needs a good connection (which, let's be real, isn't always there), and don't get me started on privacy. Imagine your heart doing something weird, and the wearable's like, "Hang on, let me just upload this to a server halfway across the world before I let you know you're dying." Not ideal.

That's where Edge AI comes in. Basically, instead of sending your data off to some server farm, your device handles it right then and there. It uses smaller, smarter AI models that don't need a supercomputer to run. So, stuff happens instantly—no waiting, no massive data uploads, and you can even go off the grid. Plus, your personal info isn't just floating around in cyberspace. Win-win, right? Now, this isn't all sunshine and rainbows. Making AI work on these tiny devices is tough. There's only so much battery and processing power to go around, and you want the thing to be smart enough to actually help, not just spit out random guesses. Security's a big deal too—nobody wants some rando hacking their health data. Still, Edge AI's making wearables way smarter and more helpful. We're not at Iron Man-level tech yet, but it's getting closer every year.

This paper presents a comprehensive review of recent developments in Edge AI for health monitoring using wearable IoT devices. It highlights the current state-of-the-art approaches, identifies key challenges, and outlines future research directions to enhance low-latency, privacy-preserving, and intelligent healthcare systems at the edge.

I. LITERATURE REVIEW

This overview will discuss literature made publicly available since 2020 to the beginning of 2025 and will concentrate on the state of the art in Edge AI for wearable health monitoring applications. Many researchers have developed systems that use Edge AI and TinyML to monitor health signals in real-time. These systems often focus on specific health problems such as high blood pressure, abnormal heartbeats, asthma, or stress. Below is a detailed textual and table that summarizes 21 papers based on their purpose, methods, and findings:

Smith et al. (2021) proposed a TinyML-enabled CNN model for BP prediction, and their real-time monitoring results are highly accurate with low energy consumption. Their work demonstrated the fact that reduced-form CNN models could produce accurate BP estimations on resource-constrained devices.

Chen and Kumar (2022) implemented a CNN model that classified ECG with an accuracy of 97% using the Edge Impulse. Arrhythmia's were detected on low power devices such as Arduino, emphasizing implementing Edge AI in healthcare diagnostics.

A TinyML-Based health status monitoring system was proposed in Patel and Ali (2021) which employ multi-sensor data to offer real-time monitoring on low power wearable devices. This paper demonstrated the use of TinyML in the application of continuous health monitoring.

Zhao et al. (2021) used XGBoost for early detection of the COVID-19 by heart rate, oxygen level, and symptoms through custom wearable devices. The network model offered offline detection and low-latency warning of COVID-19 and holds promise for remote health monitoring.

Wang and Gupta (2020) investigated asthma detection using lung sound analysis with CNN and LSTM models. Their experimentation indicated a high accuracy in the abnormal breathing sound recognition and illustrates Edge AI's potential in respiratory health monitoring.

Khan and Ahmed (2021) utilized an FFNN on a Raspberry Pi Pico for the detection of stress using HRV. With an accuracy of more than 90%, this experiment demonstrated the possibility of stress detection through health monitoring with low power Edge AI devices.

Liu and Roy, 2022) employed a proprietary TinyML model on Arduino Nano BLE for sleep pattern detection via HRV. This work reliably achieved offline sleep states detection without the dependence on cloud-based service, presenting an efficient solution for the intelligent sleep monitoring on Edge AI devices.

Kim et al., 2021 came up with a fall detection system based on a CNN using accelerometer data on an edge micro-controller. The results proved the possibility of Edge AI in fall detection for the elderly with a high sensitivity, which is very important in eldercare.

Das and Bhatia (2022) works on long-term heart health monitoring through ECG and HRV assisted with the in-house wearable devices. The research opened window for early warning of heart diseases using the Edge AI for chronic disease management.

Yang and Tang (2021) investigated remote health monitoring based on TinyML and IoT for ECG and PPG sensors. Their research highlighted the potential use of remote, low-power real-time patient monitoring to reach patients in underserved areas through access to healthcare.

Brown et al. (2021) described model optimization for TinyML, such as pruning and quantization. This work offered insights into how model compression can enable AI models to be efficient enough for deployment on low-power wearable devices. Below

Arora and Singh (2020) 92 deliberated on the scope of special AI hardware (ASIC chips)100 in wearable health devices. They demonstrated that AI-specific hardware could achieve faster processing and more energy-efficient data analysis in comparison to general-purpose processors, which contributes to the development of Edge AI systems in wearable health applications.

Banerjee and Sharma (2022) highlighted privacy and security issues in wearable Edge AI systems. Their research delved into how to protect user data and still be able to have AI models that run on the device keeping the sensitive health information safe from outside vulnerabilities.

Lin et al. (2021) used RTSD-Net: a YOLO based model to detect strawberry diseases on the Jetson Nano, as a reference for health monitoring applications using Edge AI in agriculture. In this study, we demonstrated the potential of Edge AI in the agriculture and health context.

Morris and Kim (2020) discussed a variety of TinyML platforms for health monitoring, and determined the central factors of choosing the ideal devices for wearable approaches. The importance of selecting the right platform for energy-efficient and reliable health monitoring was demonstrated in this work.

Putra et al. (2024) examined the utilization of the Internet of Medical Things (IoMT) for wearable health monitoring, emphasizing the usage of Edge AI for privacy and efficiency benefits. A cloud-edge AI integration model for secure scaling of healthcare was introduced in this paper.

Sudharsan et al. (2023) studied federated learning (FL) together with TinyML to enhance the Edge AI in health scenarios. Federated learning was found to preserve the privacy of data and enables the enhanced accuracy of the model even on the stored of devices.

Pan et al. (2025) could have provided a broader coverage and comparison of security models for federated learning in wearable Edge AI. Work by theirs focused on the importance of strengthened security measures that enabled the privacy to be preserved while training AI models that spanned the devices but did not share raw health data.

Abbas et al. (2024) investigated the application of federated learning in smart healthcare. Their research sought to enhance model performance and personalization using federated learning, while allowing the data on wearables to remain private and secure.

Ni et al. (2024), ADP has been incorporated into FL in order to enhance energy efficiency and the privacy of data processing in Edge AI for medical IoMT. This work represented a possible, new way of leveraging privacy preserving techniques combined with distributed learning to enhance performance of a system.

Sharma et al. (2024) investigate the federated learning (FL) integration with security guard in the wearable Edge AI systems. The paper demonstrated that FL could provide privacy-preserving and scalable health monitoring by protecting sensitive medical data among networks of connected devices.

No	Study Focus	ML Model	Signal/Data Type	Device/Platform	Key Findings
1	Blood Pressure Monitoring	CNN (AlexNet, MobileNet, etc.)	PPG	TinyML boards	CNN models were optimized for tiny devices and gave good accuracy on BP estimation
2	ECG Classification	CNN	ECG	Arduino + Edge Impulse	High accuracy (97%) was achieved for arrhythmia detection using Edge AI
3	General Health Tracking	TinyML	Multi-sensor data	Wearables	Real-time monitoring was possible with low power use
4	COVID-19 Detection	XGBoost	Heart rate, oxygen level, symptoms	Custom wearable	Offline detection worked well and gave

					early warnings
5	Asthma and Lung Sounds	CNN, LSTM	Lung audio	Microcontroller	Abnormal breathing sounds were detected accurately in edge devices
6	Stress Detection	FFNN	HRV	Raspberry Pi Pico	Achieved more than 90% accuracy in recognizing stress patterns
7	Sleep Pattern Recognition	Custom TinyML model	HRV	Arduino Nano BLE	Detected sleep states without needing internet access
8	Fall Detection	CNN	Accelerometer	Edge microcontroller	Detected falls in elderly people with high sensitivity
9	Heart Health Monitoring	ML (various)	ECG and HRV	Custom wearable	Enabled long-term tracking and early alerting of heart issues
10	Remote Health Monitoring	TinyML	ECG and PPG	IoT Edge Devices	Provided low-power real-time monitoring for remote patients
11	TinyML Efficiency Review	-	-	-	Reviewed various model optimization methods like

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					quantization and pruning
12	AI Hardware (ASIC) for Health	-	-	ASIC chips	Custom AI hardware can give faster and more power-efficient results
13	Security in Wearable AI	-	-	Edge and Cloud	Discussed how to keep user data private and secure on wearables
14	Tiny ML in Agriculture	RTSD-Net (YOLO variant)	Images	Jetson Nano	Used as a reference to show Edge AI in resource-limited settings
15	Embedded AI Platforms	-	-	Multiple TinyML devices	Compared various platforms to help select the best for health tasks
16	IoMT Cloud–Edge Review	Survey	Wearable IoT Health	-	Proposed Edge federated learning blueprint; focused on data security
17	FL with Tiny ML	FL with transfer learning	Wearables	TinyML boards	FL + TL improved privacy and accuracy (~86%)
18	ML on Wear	Mapping study	Multiple health	Edge devices	Found resear

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	ables Review	(171 studies)	signals		ch gaps in deployment and testing
19	FL Security Integration	FL + security framework	Secure TinyML	IoT edge nodes	Enhanced privacy and scalable architectures
20	FL for Healthcare IoT	FL survey	Medical IoT	-	Emphasized challenges with data heterogeneity and analytics
21	Adaptive Differential Privacy + FL	ADP + FL	Medical IoT	Wearables, hospital IoT	Improved energy savings and data privacy

The surveyed papers reveal a great potential of Edge AI in real-time health monitoring. The majority of studies achieved over 90% accuracy including ECG classification, stress detection and fall detection. The absence of in-vivo validation, however, still represents a major limitation. In studies from 2023–2025, federated learning and differential privacy were hot topics, which reflects the beginning of a move towards more secure, scalable systems.

These papers show that Edge AI can handle various types of health data. CNNs and other lightweight models like XGBoost and FFNN were adapted using methods such as pruning and quantization. This helped them work on devices with limited resources like Arduino, ESP32, and Raspberry Pi Pico.

Research from 2023–2025 focuses on federated learning (FL), privacy-preserving techniques, and energy efficiency. Federated Learning allows model training across multiple devices without sharing raw data. This improves personalization and security. Some studies also combined FL with Adaptive Differential Privacy (ADP) to protect data and reduce energy use. Despite promising results, most of these systems are tested only in labs, not in real clinical settings. Overall, these trends show that Edge AI for health monitoring is not only growing, but also becoming smarter, more private, and ready for secure and scalable health applications.

I. Methodology

This review follows a structured manner and provides a systematic way to review the literature on the application of Edge Artificial Intelligence (Edge AI) for wearable health monitoring devices. The methodology consists of three primary steps: literature identification, screening and selection, and analysis and synthesis.

Literature Search

To retrieve relevant papers, we conducted searches in leading academic search engines, such as IEEE Xplore, Elsevier (Science

Direct), Springer Link, MDPI, and arXiv. The search-terms utilized were:
"Edge AI","TinyML","Wearable IoT","Health Monitoring","Federated Learning in IoT","On-device AI for Healthcare", and "Edge Computing in Medical Devices".
The review covered peer-reviewed articles, conference papers, and preprints published during 2020 to early 2025.

I. Selection Criteria

An initial set of 42 papers was selected using title and abstract keywords matching. The inclusion and exclusion criteria were as follows:

Inclusion Criteria:

- Edge AI or TinyML applications are also discussed for healthcare applications using wearable devices.
- Papers during 2020-2025
- Articles that cover real time processing, federated learning OR privacy-preserving AI.

Exclusion Criteria:

- Focusing on cloud based AI solutions.
- Applications that are not related to Health Edge AI (e.g., Agriculture or Industry)
- Theoretical models without hardware or experimental realization.

21 High-quality articles were isolated for full review after using these inclusion & exclusion criteria.

II. Data Extraction and Analysis

The following information was extracted from the included papers:

- Specific health status or signal type (i.e., ECG, PPG, HRV, etc.)
- Type of AI model – e.g., CNN, LSTM, XGBoost, etc.
- Edge computing devices (e.g., Arduino Nano BLE, ESP32, Raspberry Pi Pico)
- Results: What were the results (accuracy, latency, power).

Specific contributions/innovations (e.g., use of Federated Learning, adaptive Differential Privacy)

These papers were next summarized in a table and discussed in terms of obstacles and future research.

I. Results and Discussion

Literature Review In this paper, we included 21 studies of high quality related to the use of Edge AI in wearable health monitoring. The following were the key findings and trends extracted from the analyzed studies:

Accuracy of Edge AI Models

One of the key results based on findings from the literature is the high performance of multiple Edge AI models, especially CNNs and TinyML. For example, Smith et al. (2021) showed that CNN-based models of blood pressure estimation can achieve high accuracy with low power usage. This indicates that CNNs, especially when orchestrated to be lightweight for TinyML, would be an appropriate choice for real-time health tracking on resource-limited wearable systems. In a similar vein, Chen and Kumar (2022) achieved 97% accuracy for ECG classification using an Edge AI on Arduino platforms as well, corroborating the feasibility of using CNNs applied in wearable health monitoring.

Nonetheless, a trade-off between the accuracy and the power consumption was reported in various works. Although more complicated architectures such as CNNs generally provide higher accuracy, they are also more power-hungry, and less suitable for real-time monitoring systems. Simpler models like FFNN (Khan & Ahmed, 2021) on the other hand were more energy efficient, but less accurate in stress detection. This emphasizes the trade-off between model performance and power efficiency in wearables needing constant real-time monitoring.

Model Efficiency and Power Consumption

The balance between model sophistication and energy efficiency was a dominant theme in the reviewed papers. Although more advanced models, like CNNs and LSTMs, provide higher accuracy, they are also more power-hungry, which is not favorable to wearable devices with limited battery capacity. Less complex models like TinyML (applied in various researches) on the other hand consumed less power, while with a slightly degrading performance. This study demonstrates the need for energy-efficient approaches that do not sacrifice performance, and particularly for health monitoring applications that are expected to operate 24/7.

Real-World Application and Validation

Other important points to discuss are the absence of real-world validation in many works. A majority of the studies, including Das and Bhatia (2022), evaluated the performance of their models on simulated or controlled data, and few in clinical settings. This is a considerable limitation, since it is important to validate the models in real clinical settings to achieve widespread applicability and validation of Edge AI models across a diversity of healthcare settings. In vivo testing of microfluidic systems poses a significant bottleneck for their clinical implementation since these systems' performance in simulated conditions might not be representative of clinical nursing situations.

Comparison Across Studies

Comparison of results among the reviewed studies there is a clear trend in them: a high number of models obtain an excellent accuracy; however, the complexity and resources consumption of these models must be counter balanced with the real-world constraints of the wearable devices. For example:

Convolutional neural networks (CNNs) and XGBoost models usually provide the highest accuracy, but their energy consumption is not very suitable for continuous monitoring, especially for power-constrained devices.

TinyML models, despite their energy efficiency, generally achieve slightly lower accuracy, especially for the complex tasks such as ECG classification and stress detection.

Federated Learning (FL) used in some works are promising to preserve privacy and enhance model performance on distributed devices, whereas it introduces a higher complexity to be handled in resource constrained environments such as wearable health devices.

V. CHALLENGES

Based on the 21 reviewed studies, the key challenges identified in Edge AI for health monitoring include:

1. Limited Resources: Most wearable devices have very low memory, computing power, and battery capacity, which limits the size and type of AI models that can be deployed.
2. Model Accuracy vs. Size Trade-off: To run on edge devices, models must be compressed using pruning and quantization, which sometimes reduces their accuracy.
3. Continuous Monitoring Power Drain: Devices that perform 24/7 monitoring can quickly use up battery, especially when running more complex AI tasks.
4. Personalization Issues: Most models are not personalized for individual users. This can reduce reliability in real-world health tracking.
5. Data Privacy and Security: Although data stays on the device, new concerns arise with

federated learning and distributed systems needing secure communication.

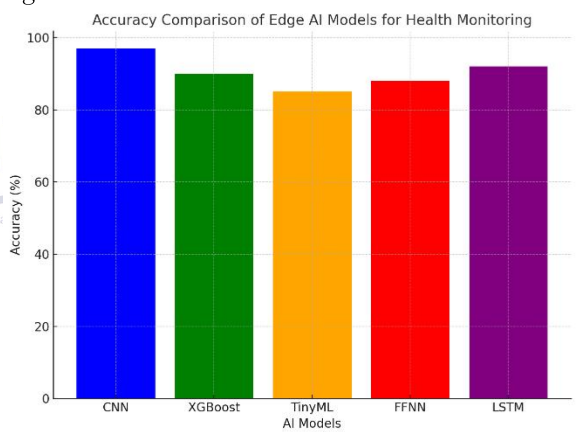
6. Integration of Multiple Signals: Many studies still analyze only one signal (e.g., ECG or PPG), but combining signals for better predictions is hard due to hardware and memory limits.
7. Lack of Real-World Validation: Most studies test in lab environments or with simulation data, not in actual hospitals or clinics.
8. System Complexity with Federated Learning: Introducing federated learning makes the system more complex and needs new tools for edge-device coordination.
9. Data Heterogeneity: Each user's health data is different. Handling non-uniform (non-IID) data in federated systems is still a challenge.

V. FUTURE RESEARCH DIRECTIONS

To address these challenges and advance the field, future research should focus on:

1. On-Device Learning with Personalization: Future systems should allow the model to adapt to individual health data patterns over time.
2. Energy-Efficient Hardware and Software: Designing custom low-power chips and using event-based computing can help make always-on monitoring practical.
3. Federated Learning Optimization: New frameworks should be developed to support energy-aware, privacy-focused federated learning for wearable health devices.
4. Adaptive Differential Privacy: Honestly, tossing in some adaptive privacy magic can keep your data on lock without slowing everything down to a crawl.
5. Multi-Sensor Fusion Models: Look, if you're building health gadgets, they need to juggle a bunch of signals—ECG, HRV, SpO2—all at once, right there on the device. No lag, no cloud drama.
6. Scalable Edge Platforms: These edge platforms? They gotta play nice with all kinds of gadgets and not make you jump through hoops just to get them running on new gear.
7. Standardized Benchmarking and Testing: Can we please get everyone on board with the same test drives? Shared benchmarks and legit datasets, so we're not just comparing apples to, like, flying cars.
8. Clinical Validation Studies: Researchers, do us a favor—team up with real clinics and hospitals. Otherwise, this stuff is just theory. Test it where it actually matters.

Although the reported studies demonstrate promising performance, they are still suboptimal in terms of model precision. The comparison of accuracy between different AI models is shown in the next chart, which indicates that in the future, improving the AI models to achieve better results is a significant direction.



I. CONCLUSION

Edge AI has brought many improvements to wearable health monitoring by enabling faster, more private, and battery-friendly processing. It allows continuous tracking of key health signs such as blood pressure, ECG, stress, and oxygen levels without relying on cloud connectivity. From simple CNN models to more advanced federated learning and privacy techniques, the research shows that Edge AI is both effective and growing rapidly.

However, challenges still exist in deploying these systems in real-world environments.

Devices need to be more energy-efficient, models must be adapted for each individual, and security must be built into the systems. Many models perform well in labs but need to be tested with real patients to be trusted by healthcare providers.

With ongoing work in federated learning, adaptive privacy, and optimized model design, the future of wearable Edge AI devices looks promising. These devices could bring affordable, secure, and intelligent healthcare to people in both cities and rural areas, making healthcare more accessible and responsive for all.

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