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Edge-AI Meets the Heart: Real-Time Cardiovascular Monitoring with Cloud-Connected Wearables

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Abstract

Cardiovascular diseases top the list of killers in the world, and to that death, a great part of responsibility could be assigned to arrhythmias, tachycardia, and heart failure. Conventional approaches of long-term tracking, like Holter monitors and ECGs in a hospital, excel in

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giving restricted continuous information. Wearables, along with Cloud computing and Edge AI, are a breakthrough in real-time cardiovascular monitoring that has the potential for early detection and intervention. The review critically evaluates the role of Edge AI in wearable gadgets to measure real-time cardiovascular data, specifically arrhythmia, heart failure, and tachycardia management, and also reflecting on the role of cloud-based systems in predictive analytics and individual therapy. The search was methodically done in Google Scholar, PubMed, and Web of Science using Boolean search queries, and studies published during the period between 2015 and 2025 were also sought. The survey on the 937 articles narrowed down to 34 articles on their relevance and quality. CNNs and RNNs reached a diagnostic accuracy ranging between 85-98% in cardiovascular anomalies with only an edge AI model. The privacy issue was solved by federated learning, whereas personalized treatment and real-time processing became achievable with cloud integration. Edge AI-enabled wearable devices enable effective real-time cardiovascular health monitoring, but the issues of privacy of the data, sensor performance, and optimality of the model are still unresolved.

Keywords: Edge AI, Cardiovascular monitoring, Real-Time ECG analysis, Cloud-Connected healthcare, Systemic review.

1. INTRODUCTION

The most widespread causes of death in the world are the causes of cardiovascular diseases (CVDs), as every 32 deaths, which are found in accordance with the data presented by the World Health Organization (WHO), and the report it published in 2019. Coronary artery disease, heart failure, and arrhythmia are a few CVDs that do not exhibit any symptoms at his initial stages. The majorities are not aware of their situation until their fatal conditions occur in the form of heart attacks or sudden cardiac arrests. The development of cardiovascular anomalies is one condition where early diagnosis is crucial in averting the acute events to enhance patient outcomes.

Comparatively, non-routine monitoring methods such as the Holter monitors and regular ECGs, conducted in the hospital, are not as effective in case of prolonged and round-the-clock monitoring. Acutely vulnerable, Holter managerial has been intended to spot irregularly occurring cardiac issues within a 24-72 hour evaluation interval. In addition, the remote and underserved populations in which there is no consistency of access to temporary medical treatment cannot be reached through traditional means. Therefore, there exist growing needs of enhancing continuous real-time monitoring processes to identify cardiovascular anomalies remotely to enable measures to be taken promptly and the appropriate form of care be customized [1].

There are some of the solutions to this challenge that have been propagated by the recent developments in the wearable technology. Advanced cardiovascular monitoring can be provided on a continuous and real-time basis by devices such as smartwatches, biosensor regular patches, and textile sensors. Certain of them can track such vital signs as ECG, heart rate variability (HRV), and blood oxygen saturation level (SpO2), which means that it is possible to constantly access data related to the patient as never before [2]. With the implementation of edge-AI (integration of Artificial Intelligence (AI), these devices would be able to process the information on the device (like a smartwatch) itself without being immediately required to upload it to the cloud. The on-board data processing minimizes latency and bandwidth making it possible to have real-time diagnostics performed even with limited resources [3].

Artificial intelligence is no longer an aspect of retrospective inquiry into patient data, but real-time detection and prediction on a cardiological basis. Initial studies in AI models used to analyze ECG were based on offline learning based on the training of massive data sets with the aim of discerning the patterns that result in the prediction of cardiovascular diseases. On the contrary, Edge-AI considers such models to be executed directly on an ambiguity-wearable device allowing to suggest predictions without the use of cloud access. The possible overall latency decrease is enormous to allow real-time interventions including permanent immediate notification against observed anomalies, to the patient or the physician [4].

When writing this review, we have taken into account the integration of Edge-AI in wearable devices to perform a continuous cardiovascular monitoring in real-time. This review answers the following research questions:

- How exactly does Edge-AI get infused into wearable technologies to allow for cardiovascular real-time monitoring?
- To what degree do Edge-AI-based wearable devices detect cardiovascular abnormalities, including arrhythmias, tachycardias, and signs of heart failure?
- How are AI models used for real-time measurements on sensors, such as ECG, HRV, and PPG, within wearable devices for cardiovascular abnormalities detection?
- What is the technical performance of Edge AI-based wearable cardiovascular monitoring systems in terms of accuracy, latency, and energy efficiency?
- What is the available evidence regarding the clinical utility of AI-controlled wearable devices for cardiovascular monitoring in real-time?
- What are the existing privacy, security, and data protection concerns expressed in the use of Edge-AI technology-based wearable cardiovascular monitoring devices?
- What are the challenges in the practical and clinical applicability of implementing the Edge-AI technology-based wearable cardiovascular monitoring systems?

2. LITERATURE REVIEW

The management of the cardiovascular health by the wearable technology has evolved over several decades. The first shape of Holter monitors that were released in the 1960s had the capability of recording ECG data over a period of 72 hours. They were valuable tools in the diagnosis of the arrhythmias and other heart diseases but they were not so effective because they were short in duration of monitoring and were bulky and so difficult to have long [1]. Although useful in short time monitoring, they were replaced by the continuous long-term cardiovascular surveillance due to the requirement of often analyzing the data, and also caused discomfort to the patient due to the size and wiring of the device.

With the development of technology, another wave of less objectionable would be among the athletes and fitness enthusiasts was suggested; strap-on chest heart rate meters. The devices of this type however did not consider the critical diagnostic information needed to measure arrhythmia or heart failure and as such, served only to monitor heart rate.

History of wearable cardiovascular monitoring became of age difference or so with smart watches such as Apple Watch Series 4+. These devices that have incorporated ECG sensors enable them to plot the heart activity on the fly, make records of ECG rhythms as well as be alerted of irregular heart rhythm [5]. Smartwatches also offer continuous monitoring of ECG and one-time monitoring of ECG. Their easy format of use renders them truly accessible to the general population, and not only to the symptomless users. Moreover, wearable biosensors patches like ZioPatch allow long-term surveillance, with minimum inconvenience; the biosensor patches are an even less obtrusive option to terminally invasive Holter devices. Thus, these patches can be of great assistance to enhance patient comfort and adherence because they offer patients with a non-invasive way of prolonged cardiovascular monitoring as long as days or weeks [6].

Edge AI has transformed the industry of wearable health devices, allowing real-time processing of all information on the machine. Edge AI can be defined as computing data near to the source without uploading the data on a central cloud server. In this case especially in emergency scenarios such as that of arrhythmia and heart failure, a quick response is crucial to patient safety. Efforts to use Edge AI make it easier to capture and make decisions in a matter of milliseconds and no longer wait while a process that is more time-consuming, like data transfer to the cloud storage, and subsequent reappearance, after the analysis have taken place, to implement some action [7].

ARM Cortex-M and Google Coral - architectures were also created with the aim of supporting AI model execution on low-resource devices such as an unlimited number of wearable ECG monitors, biosensors deployed, etc. These hardware solutions are designed in such a manner that they are low-power, high-performance of real-time activity and introduce an analytic procedure and reduce the charge on the battery utilized. Additionally, standards of AI models to shrink their size and complexity due to TinyML and model compression such as quantization and pruning are used in the vehicle at its edge. In essence, under these methods, the performance of models on low-power appliances do not suffer, and hence they can always run to monitor their health continuously [8].

Over the years, the capabilities of Edge AI in detecting the arrhythmias have been significantly enhanced. Some research studies have used different deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to engage in real-time analysis of ECG signals on wearable devices. These methods have demonstrated outstanding diagnostic performance, with a sensitivity of 85-98% hence making it easy to assess the risk of a heart attack in real-time [9].

These models are usually trained under MIT-BIH Arrhythmia database and PTB-XL data set which operates the correct positioning of arrhythmia detection in practice. Through such models, edge devices can do real-time ECG analytics, abnormal rhythm detection, and prompt alerts to the patient or the healthcare provider when necessary. The fact that it can locally distribute ECG data and compute analytics within the latency of less than 100 ms, which is profoundly crucial in the case of on-time intervention being required to avoid severe cardiovascular complications such as sudden cardiac arrest is a big strength of Edge AI.

Simultaneously, FL and Transfer Learning start to get relevant to ensure that the privacy of patient data stay unimpaired and AI models continue their development. In FL, the model is trained on each device belonging to an individual and the updates of the raw data are never changed, just the model updates-the raw data are sent to the central cloud to aggregate. This implies that patient information is not going to be out in the middle of the server, thereby guaranteeing the safety of patient data and at the same time enabling the constant enhancement of the model. That is why, in the context of health care that is characterized by high security and confidentiality needs, these algorithms can be of great importance [8]. In addition, EHRs and longitudinal data used in cloud environments provide personalized predictive analytics, in which the healthcare can actually control the treatment plan depending on the personal history of the individual on account of his or her health.

These and some other commercially adjustable wearables have been clinically validated and used to detect arrhythmia, including the KardiaMobile and Fitbit ECG. They have been found to be able to achieve diagnostic levels of performance comparable with more traditional Holter monitors and clinical electrocardiogram (ECG) systems, and sometimes higher. Thus, as an example, Apple Watch Series 4+ has been studied and confirmed with regard to its ability to read atrial fibrillation with the same accuracy and highest values up to 98. The question is however on what the patients adhere to when it comes to the wearing of the devices and their distribution in rural facilities which have limited access to medical care.

The challenges resulting in opposition to the wholesale introduction of such portable devices as the tools of heart watch include such factors as prices, comfort, and the availability. Edge-first models are especially relevant to scarcity-based environments where a constant internet connection is not required, and where it can be located in remote locations. Regardless of these encouraging findings, more efforts are required in shaping the devices, transmitting of data and patient education to ensure that underserved and rural regions can access these devices [9].

3. METHODOLOGY

This was a systematic review that was conducted in line with the PRISMA 2020 guidelines on evaluating the value of Edge AI and Wearables to track cardiovascular phenomena in real time, namely heart failure prediction, arrhythmia and tachycardia detection. The purpose of the present review is to explore the creation of a new system which would monitor and detect cardiovascular anomalies continuously and at early stages: Ot wearable devices, Edge AI and distributed cloud systems. The types of applications that are explored by this review are a broad selection of technologies related to AI: deep learning, machine learning (ML), and predictive analytics.

Step 1: Identification

The initial phase of the identification process was to conduct an extensive search of Google Scholar, PubMed, IEEE Xplore, and Scopus to ensure that a wide range of appropriate literature was obtained regarding the Edge AI with real-time cardiovascular monitoring. This search was conducted on October 15, 2025. The given search string was used in all of the databases (TABLE 1):

("Edge AI" OR "wearable devices" OR "smartwatches" OR "biosensors") AND ("real-time cardiovascular monitoring" OR "heart failure prediction" OR "arrhythmias detection" OR "tachy-

cardia") AND ("cloud-connected healthcare" OR "distributed cloud systems" OR "predictive analytics heart monitoring" OR "ECG analysis") AND ("privacy-preserving architecture" OR "health data security" OR "low-latency AI") AND ("telemedicine" OR "remote health monitoring")

Table 1: Summary of Search Strategy and Keywords

No.	Construct	Search Field/Limits
1	"Edge AI" OR "wearable devices" OR "smartwatches" OR "biosensors"	Topic (TS)
2	"real-time cardiovascular monitoring" OR "heart failure prediction" OR "arrhythmias detection" OR "tachycardia"	Topic (TS)
3	"cloud-connected healthcare" OR "distributed cloud systems" OR "predictive analytics heart monitoring" OR "ECG analysis"	Topic (TS)
4	"privacy-preserving architecture" OR "health data security" OR "low-latency AI"	Topic (TS)
5	"telemedicine" OR "remote health monitoring"	Topic (TS)
6	2015–2025	Publication Year (PY)
7	Language: English	Language Restriction

The search procedure was conducted in different databases targeting studies published in the following range 2015-2025 and received 937 articles. The 10 year time frame was selected because of the wearable technologies in healthcare. Although, AI has been introduced to cardiovascular recently, but wearable technologies have been in use since a long time. Articles regarding wearables, AI use, and cardiovascular health in English were searched to address all the areas of these points in the literature.

Step 2: Screening

This process was preliminarily screened by the two independent reviewers checking the titles of the 937 articles as to whether they could be further considered as eligibility in the research. Relevant articles were to be included and the criteria applied included:

- The importance of AI-based solutions in real time monitoring of cardiovascular conditions through the utilization of wearable devices or bio sensors was stressed.
- AI methods were explained as licensed to detect arrhythmia, predict heart failure, detect tachycardia or forecast analytics in cardiovascular care.
- The articles have reported or have executed or actually practiced cloud related health care systems or distributed cloud platforms in carrying out real-time data processing or telemedicine applications.

A systematic literature search was conducted and a total of 937 literature items were identified. All identified articles were screened based on their titles, and a total of 537 articles were excluded due to irrelevance, given in TABLE 2. The remaining 400 articles were then screened based on their abstracts, and 225 articles were excluded for not meeting the selection criteria. Finally, 175 articles were subjected to eligibility assessment based on their full text, and 34 articles were included that met all selection criteria.

Step 3: Eligibility Criteria

Up till the moment, the eligibility criteria have been formulated in such a way that the best and most relevant studies would be considered. There were inclusion and exclusion criteria as shown in TABLE 2:

Step 4: Inclusion

Thirty-four selected articles were exhaustive in data extraction and synthesis. The research was gathered meticulously with respect to significant matters as purpose and research questions from the particular study, the specific artificial intelligence models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), deep learning architecture, AI systems based on transformer models, etc. for which datasets were used for training and validating the models-so prominently MIT-BIH Arrhythmia Database along with many proprietary databases. Performance metrics such as accuracy, sensitivity, specificity, latency, and Area Under the Curve (AUC) were carefully recorded for effectiveness. Furthermore, an examination of the clinical importance given by these AI techniques was done specific to their virtual medicine and cloud-based collaborative computing systems bringing in real-time opportunity in cardiovascular caregiving. The entire selection process of study is illustrated in FIGURE 1, in line with PRISMA.

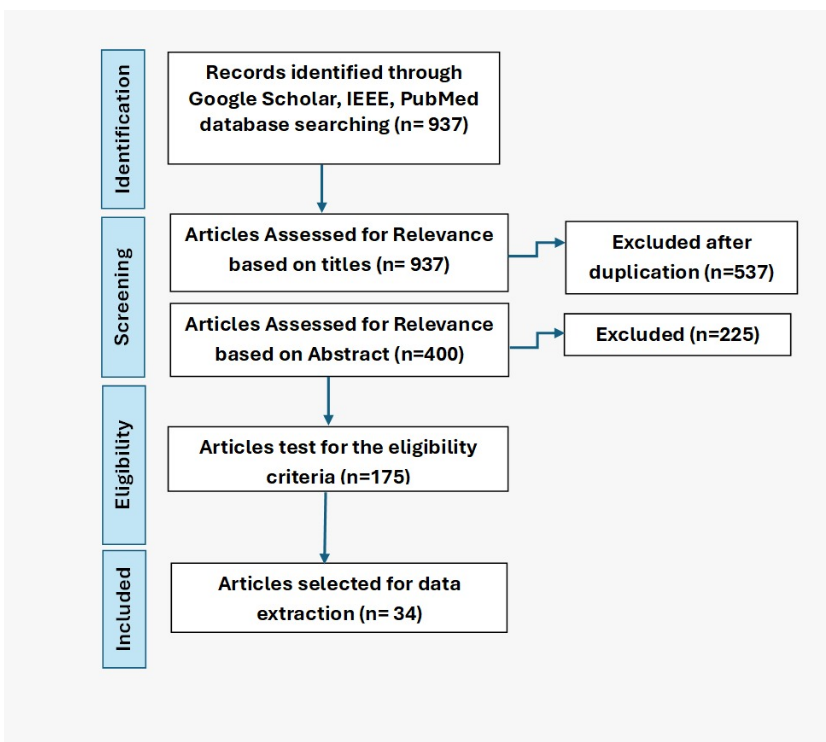

Figure 1: PRISMA Flow Diagram for Systematic Review Study Selection

Table 2: Eligibility Criteria for Review

Criteria	Inclusion	Exclusion
Timeframe	Studies published between 2015 and 2025	Studies published before 2015
Peer-Reviewed	Only peer-reviewed articles	Non-peer-reviewed articles, preprints
Focus Area	AI-based wearable devices for cardiovascular monitoring, including ECG, HRV, arrhythmia detection, heart failure prediction, and tachycardia detection	Studies unrelated to wearable devices or AI-driven cardiovascular monitoring
Language	English or translatable into English	Non-translatable languages
Technology Focus	Studies discussing the integration of Edge AI with cloud-connected healthcare systems, real-time data processing, predictive analytics, and privacy-preserving models	Research that does not focus on the integration of Edge AI and cloud systems in cardiovascular monitoring
Health Focus	Studies on real-time cardiovascular monitoring, predictive analytics, and heart anomaly detection using wearable devices	Studies focused on non-cardiovascular health issues or non-wearable AI applications
Clinical Focus	Studies that discuss the clinical applicability and validation of wearable devices for real-time cardiovascular monitoring	Research that does not include clinical validation or real-world applicability of the devices

The AI methodologies, datasets, and performance metrics have been assembled from each of the studies selected. Analysis on the performance of AI models, including CNNs and transformers, considers accuracy, sensitivity, and specificity, and they ranged from 85% to 98% model performance [7]. Some of the challenges mentioned in the literature include issues of data heterogeneity and trust, and there are applications that integrate privacy-preserving learning models like Federated Learning [7].

The present systematic review synthesizes findings related to multiple domains of Edge AI and wearable gadgets in cardiovascular health monitoring and gives insight on technical performance, clinical significance, and privacy issues concerning real-time cardiovascular monitoring systems.

4. RESULTS AND DISCUSSION

TABLE 3 presents a summary of AI-integrated wearable devices for cardiovascular monitoring.

Table 3: Summary of AI-Integrated Wearable Devices for Cardiovascular Monitoring

No. of Refs.	Type of Wearable	Sensing Modality	AI Model	Deployment Architecture	Key Findings	Conclusion
[2]	Wearable HRV devices	HRV, ECG	Not specified	Cloud	Wearables provide continuous, real-time data on HRV and ECG. Integration of HRV in diagnostics improves risk stratification for cardiovascular diseases.	Wearable HRV and ECG devices have potential for early detection, but more targeted studies are needed.
[6]	ECG Patch	ECG	Not specified	Hybrid (Edge/ Cloud)	Developed a low-power ECG patch that transmits data to the cloud for analysis. Focus on real-time monitoring with minimal power consumption.	The low-power ECG patch shows promise for continuous monitoring in ambulatory care settings.
[3]	Wearable IoT devices	ECG, HRV	Various ML models (not specified)	Edge/ Cloud	Edge AI can significantly reduce latency and improve wearablesâ□^{TM} efficiency. Models applied to ECG and HRV help in detecting cardiovascular abnormalities.	Edge AI integration in wearables can lead to more responsive and efficient monitoring systems.
[10]	ECG-based wearable	ECG	Hybrid CNN + Cloud	Hybrid (Edge/ Cloud)	Hybrid edge-cloud model improves latency and data processing. The system effectively detects arrhythmias with high confidence.	Hybrid models offer efficient processing for ECG-based wearables, combining edge and cloud benefits for real-time analysis.
[4]	ECG-based wearables	ECG	Not specified	Embedded (Edge)	Embedded AI enhances real-time ECG analysis and monitoring. Offers efficiency in continuous, on-device monitoring.	The shift from cloud to embedded AI in wearables enhances real-time capabilities, reducing latency and dependency on cloud services.
[7]	Wearable IoT sensors	ECG	Hybrid (Edge + Cloud AI)	Hybrid (Edge/ Cloud)	SmartCardio system integrates edge AI with cloud to predict cardiac risk. Offers real-time feedback for patient management.	Combining edge and cloud AI provides an effective platform for **predictive** cardiac health monitoring.
[9]	ECG-based wearable	ECG	CNN	Edge	Edge-AI wearable detects diabetes-related ECG abnormalities. Utilizes lightweight CNN models for on-device analysis.	The wearable shows promising results for multi-condition monitoring, enhancing the utility of ECG devices for more than just cardiovascular health.
[11]	ECG wearable	ECG	CNN	Edge	Edge-based ECG anomaly detection system operates in real-time, achieving high accuracy for arrhythmia detection.	Edge AI is highly effective for real-time ECG analysis, supporting timely medical interventions.

continued..

No. of Refs.	Type of Wearable	Sensing Modality	AI Model	Deployment Architecture	Key Findings	Conclusion
[8]	ECG-based wearable	ECG	Lightweight CNN	Edge	Lightweight CNN model for real-time detection of ECG abnormalities. The system works efficiently on low-power wearable devices.	Edge AI offers an optimal balance between diagnostic accuracy and resource limitations for wearables.
[12]	Smartwatch	ECG	Not specified	Edge	Real-time ECG monitoring for early heart attack detection. Smartwatch alerts the user in time to seek intervention.	Wearables can play a critical role in early heart attack detection and prevention when coupled with AI.
[13]	Not specified	ECG	Not specified	Cloud	The study focuses on genotype prediction for hepatitis, suggesting broader applications of AI in precision medicine.	While not directly related to cardiovascular health, this study highlights the potential of AI for personalized healthcare solutions.
[14]	Smartwatch	ECG	CNN	Edge	Smartwatch successfully detects **idiopathic ventricular tachycardia** with high sensitivity.	Smartwatches with embedded AI models can detect arrhythmias accurately, enabling early diagnosis and prevention.
[5]	Cardiovascular monitoring wearables	ECG, PPG	ML Algorithms (not specified)	Hybrid (Edge/ Cloud)	The AI-enhanced healthcare IoT system offers real-time cardiovascular monitoring with high accuracy.	Cloud-edge systems are effective in monitoring cardiovascular health in real-time.
[15]	Wearable sensors	ECG, PPG	AI models for arrhythmia and stroke prediction	Edge	Wearable sensor-based AI models effectively predict both arrhythmias and stroke risk in real-time.	Edge computing in wearables can significantly improve diagnostic capabilities for both arrhythmias and stroke prevention.
[16]	Smartwearables	ECG, PPG	Not specified	Hybrid (Edge/ Cloud)	AI-powered wearables are capable of detecting a wide range of cardiovascular diseases with high accuracy.	Smart wearables with integrated AI provide a reliable method for continuous cardiovascular health monitoring.
[17]	Smartwatch	ECG, PPG	Not specified	Edge	Smartwatch successfully detects heart attack symptoms early and triggers timely alerts.	Smartwatches with AI are effective in predicting heart attacks and improving patient outcomes.
[18]	ECG-based wearable	ECG	AI models for arrhythmia detection	Hybrid (Edge/ Cloud)	AI-enabled wearables improve diagnostic accuracy for arrhythmias and enhance remote monitoring.	AI-driven wearables are critical for enhancing diagnostic capabilities in arrhythmia detection.
[19]	Wearable IoT sensors	ECG	Deep Learning	Edge/ Cloud	IoT-based wearable sensors combined with DL models offer accurate heart health monitoring.	Wearable IoT systems with deep learning can provide efficient and accurate cardiovascular monitoring.

4.1 System Architecture: Edge-to-Cloud Pipeline

4.1.1 Data collection and preprocessing

Wearable cardiovascular monitoring systems collect a variety of data including electrocardiography (ECG), photoplethysmography (PPG), and other sensors used in conjunction with an accelerometer and SpO2 sensor data. The measurements obtained from these sensors include continuous heart rates, rhythms, oxygen saturations, and vital signs. Nonetheless, the raw data is often badly corrupted with noises generated by artifacts due to movement, electrical interference, and environmental interference.

Preprocessing is the necessary activity for preparing data for analysis. In general, hearty methodologies for employing wavelet transforms, FFT, or Butterworth filter techniques suit noise removal. In this sense, in fact, the system achieves the desired objective whereby it extracts the heartbeats and the unwanted noise from the quality-enhanced data before proceeding into the next phase for feature extraction [17]. It allows edge preprocessing for segmentation, analyzing data intervals, heartbeat normalization such that data from all devices and users become standardized [20].

Moreover, Edge Preprocessing at the wearable device level is very critical because it would perform the data segmentation that cuts the continuous data stream into manageable segments and makes them more qualified for detailed analysis. Besides, heartbeat normalization will then ensure that measurements will be internalized in relation to different users and devices thereby standardizing the data and minimizing variability. This preprocessing step prepares the actual data for feature extraction and subsequent application in AI models [21,22] These operations are what enable real-time analysis by the wearable devices, maintaining the integrity of the data so as to be accurate in the monitoring of cardiovascular health.

4.2 On-Device Inference

Once preprocessing has been established, lightweight AIs place on-device inference to allow anomalous detection while wearing the device. Generally, the models designed for this use case are relatively light in memory and energy efficient since most work under CNNs, RNNs, and LSTMs.

For example, with model compression by pruning, quantization, and knowledge distillation, such models are small and with reduced complexity, thus being able to run properly on constrained resources [23]. Popular frameworks include TensorFlow Lite and PyTorch Mobile, while smaller frameworks tailored for ultra-low-power devices ensure that AI models are up to performance and efficiency in deployment like uTensor and TFL Micro.

Edge devices process data inside the device and are able to classify normal from abnormal beats with immediate feedback and alerts [24]. This real-time decision making is very crucial in a health care establishment where patients could be rescued in the event early diagnosis is made particularly in cases of emergency such as sudden arrhythmia episode [7].

4.2.1 Cloud integration

The role of edge computing is real-time anomaly detection, and the role of cloud computing is aggregation of data in the long term, performing remote upgrades, and retraining of models. Cloud systems aggregate data from different devices, thus keeping historical data, and run computationally heavy models for predictive analysis.

Cloud systems also undertake the integration of Electronic Health Records (EHRs), giving a full view of a patient's health history from which predictive models can be personalized [25]. Cloud platform alert systems can be deployed to send real-time alerts to caregivers, clinicians, or even family members whenever abnormal readings are detected.

Federated Learning (FL) thus becomes increasingly relevant to maintain privacy while permitting models to update continuously. In this case, local data on edge devices train the models, and only model updates (not raw data) are sent to the cloud for aggregation and retraining. Thus, sensitive health data will not leave the edge device and thus will provide an additional layer of privacy protection while the model will also get improved over time [11].

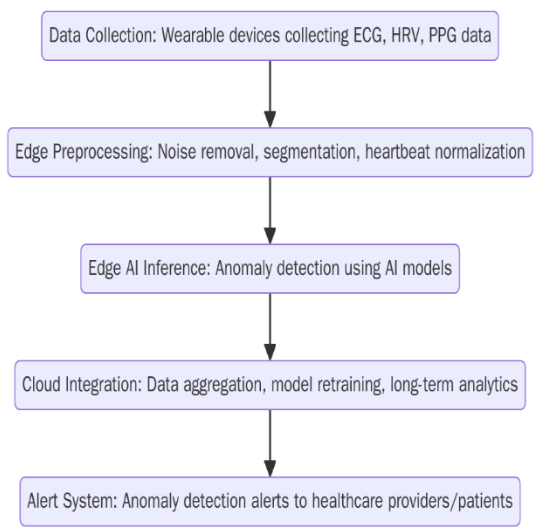

Figure 2: Edge-to-Cloud Data Pipeline Flowchart

The scope of real-time synchronization of edge devices with cloud platforms for both immediate detection of anomalies in wearable cardiovascular systems along with long-term data analytics becomes very clear here. AI incorporated IoT health monitoring systems target preprocessing ECG and other vital signals using lightweight edge models, with intensive computation activities performed by the cloud-the most important backdrop to this is [24,25]. The proposed system architecture can support delay-tolerant data transmission that allows the continuous usability of wearable devices in rural or low-connectivity environments, followed by cloud syncing as soon as the connectivity is restored (FIGURE 2). This model is very pertinent to the implementation of cardiac monitoring systems in under-resourced areas that cannot guarantee continuous connectivity. Affected devices can still communicate among themselves as part of the model. It ensures on-real-time uploading data automatically as soon as the connection is restored. Unlike most ubiquitous wearable health systems today, which are mainly model-heavy and require more cloud use, weightless edge-based models support systems in their operability when there is no communication with a potential destination health information cloud.

4.3 Evaluation Metrics and Clinical Relevance

4.3.1 Technical metrics and diagnostic metrics

There are several technical metrics that it would be critical to take into account to assess both the efficiency and efficacy of a system for wearable devices for cardiovascular monitoring. Latency, which refers to the schedule that elapses between data collection, detection, and alert generation, is one among them. Edge systems will have latitude levels, usually ranging from about 10 ms to 100 ms, showing a very responsive character. In contrast, cloud-based systems usually have a latency between 1 and 5 seconds, which is usually not conducive for true real time monitoring and responsiveness [23].

The other very important parameter is throughput, which is the amount of data a system is exposed to at a certain time period. Of particular concern to this is the case of technologies that are continuous monitoring of the crucial cardiovascular signals because they generate enormous amounts of data that require quick and accurate processing. One more crucial factor is the battery life since wearables should not only have the ability to save their power, but also provide higher processing capabilities. Tiny-ML or compression methods sensitive to power can run several days or weeks without the use of a charging device, therefore introducing additional comfort and safety to the user with regards to long-term monitoring.

Bandwidth consumption plays a very pivotal role in distant environments where the connection is not prevalent. Edge processing reduces the tendency of the machinery to transmit data to centralized points as far as the servers are concerned hence conserving on massive bandwidth. The efficiency also enables the ability of low monitoring of a wide area and saves network resources and offers privacy.

The performance metrics most frequently used to study the diagnostic accuracy of wearable devices include sensitivity, which is defined as the percentage of correctly identified true positives concerning correctly detecting arrhythmias; specificity, which quantifies a percentage of true negatives correctly identified in order to ensure that normal rhythms are not falsely flagged; and the Area Under the Curve (AUC), which is recognized as an effective measure of a model's ability to effectively separate the positive and negative classes. Also mentioned is the F1 score, whose harmonic meaning of precision and recall works to give a fair view of a model's ability to lower false positives and false negatives.

Achievements in Edge-AI models have been, by large, very good, with often high sensitivity levels between 85 percent and 98 percent and low latency levels of less than 100 milliseconds. These aspects significantly contribute to their use in clinical scenarios in real-time when timely actions and correct tracking are required [9].

4.3.2 Usability and adoption

Enormity can be put in terms of wearable device as far as patient engagement is concerned. Patient adherence measurements, comfort, and form (size) (weight) and wearability are some of the measures that have a great influence in adoption of these technologies. The consequence of numerous forms is that comfort is a determinant factor of long-lasting utilization and, consequently, specific types of programs must always be put on [8].

Another major problem is clinical workflow integration. Coupled wearables, which can be incorporated into outpatient or regular hospital care, have high chances of becoming a normal practice, including real-time cardiologist dashboard or peri-discharge remote telemetry [12].

4.4 Privacy, Security, and Ethics

With the introduction of artificial intelligence in health care, there lies an urgent association concerning the wearables such as privacy and security. Regulatory frameworks that can be mentioned are HIPAA in the U.S. for health services and the GDPR in the wider EU, both of which develop rigid employments for the handling of patients and their records. Guidelines require encryption of data, user consent, and data residency. Under all these pieces of legislation, the handling, storage, and transmission of health data remain secure from potential breaches and theft of identifiable data.In reducing the privacy risks that are posed, FL and Homomorphic Encryption are seen as the best approaches. In FL, models are trained on devices, while all updates are sent to a hub; in this way, data remains private to the owner. With Homomorphic Encryption, it is possible to perform operations on encrypted data without exposing sensitive data [7].

With the integration of AI models into healthcare, ethical aspects come under consideration for explainability, transparency, and biases. Explainability means that the decisions by an AI model should be understood by clinicians and patients alike, and this becomes paramount for the acceptance of technology in clinical decision-making.

Biased predictions result when the AI models are built upon unbalanced or unrepresentative training datasets. This is indeed important for the prediction for the unrepresented population. There may be false alerts or detections, leading to unnecessary interventions or missed opportunities for intervention [17]. Scientists discussed how integrating AI with immune biomarker analysis supports precision medicine approaches. Likewise, combining Edge AI with wearable cardiovascular monitors personalizes treatment by continuously analyzing real-time physiological data. [26]

4.5 Deployment Scenarios and Use Cases

4.5.1 Hospital and outpatient monitoring

Robotics The new cardiovascular care featuring Wearable Devices with Edge-AI and Cloud platforms provides both in -hospital and out-of-hospital patients with procedures. The integration of the technologies has already achieved the enhancement of the clinical outcomes and efficiency of

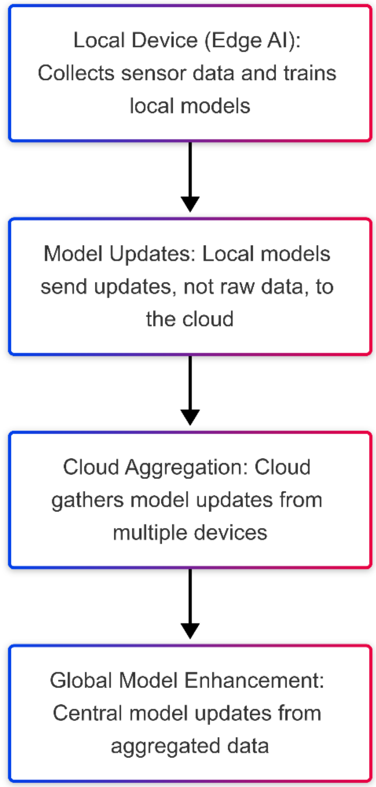

Figure 3: The diagram indicates that wearable devices can locally train AI models and transmit updates to the cloud, which does not violate the privacy protection.

its operations due to the use of continuous real-time monitoring (FIGURE 3). As an example, it is not hard to monitor the ECG values, the variability of the heart rate (HRV), and the level of blood oxygen saturation by using smartwatches and biosensor patches. This way anomaly can be detected early or any medical intervention taken in time.

Dashboards in real time provide a clinician with a comprehensive and current picture of the cardiovascular condition of a patient in the environment of the hospital. Here is an example ECG anomalies and arrhythmias were proven to be recorded on Apple Watch; it goes so far as to give warnings via on-device Edge AI [27]. This system, through inference on the device, consequently lowers the latency of providing an instant alert to the critical care settings, e.g., ICU, where reactions are to occur promptly [2].

The application of these intuitive devices is also not restricted to a hospital discharge since the devices can be used to record and monitor patients by use of telemetry beyond a hospital. As an example, ZioPatch is able to log the data 24-hourly up to 2 weeks and transmit it via cloud systems where practitioners can view and trace any observed signals with the readings of that patient [6]. The system notifies the health care personnel when an anomaly is identified and minimizes the readmission chances and maximizes patient safety.

Wearables extend the new dimension of follow-up care that was already developed by teleconsultation hence eliminates unnecessary hospital visits. Patients, who have undergone clinical procedures such as angioplasty and bypass surgery are made to be remotely monitored so that they can also receive clinical guidance even at home. The practice, which was being reinforced throughout the period of the COVID-19 pandemic, is material in creating limitations to the exposure chance in hospitals and continuity in care [8].

4.5.2 Rural and low-infrastructure areas

The use of Edge-I enabled wearables in rural and underserved communities presents some intriguing challenges related to a low level of internet and cell coverage. Older cloud-based systems cannot perform well in these environments, but otherwise, Edge-first models that do local data processing on the device are excellent competitors to a solution.

Directly, wearable devices executing AI algorithms enable Edge-AI real-time tracking of key metrics, such as ECG, heart rate, and SpO 2, which are unnecessary when connected at all times. ECG and PPG sensors of Smartwatches can be used to identify arrhythmia, such as atrial fibrillation or tachycardia, and guarantee the detection of any anomalies on time [23].

In case of the irregularity, alerts may be delivered through SMS or local networks to receive instant medical advice even without any medical facility around the location. This is the most important attribute of local processing that strengthens the system against unreliable network environment and reliable [1]. In addition, delay-tolerant transmission of data on wearable devices means that any data collected will one day when connection is restored, be synchronized into the cloud so that it can be stored or be analyzed further.

The wearables also have the ability to get data to store it locally and automatically transfer it when stronger signals become available. This synchronization mechanism is a feature of the cellular system that guarantees one that important health data will not be lost even in the case of poor infrastructure [5]. These attributes position. Continuous decentralized health monitoring is supported by edge-AI wearables and leads to better access, engagement, and outcome in remote environments.

4.5.3 Smart public health integration

The probability of greater cardiovascular disease management in the population, as a result of adoption of national health systems of Edge-AI-enabled-wearables, is high. The main suggestion of these tools is to enable real-time monitoring; consequently, it may conserve resources individually, and even enable the surveillance of the disease, an early identification of trends, and evidence-based policymaking. The streaming of real time data to a centralized national cardiovascular registry will enable the government to know high risk locations and individuals to increase restrictions on targeted interventions and resource distribution [28].

Wearable data also develops a platform to conduct enormous epidemiological research based on which the secular distribution of cardiovascular diseases can be established across the different gradients of population groups [29]. The correlation of wearables with telemedicine platforms can enhance distance diagnosis in rural or underserved communities where patients are able to transmit real time data to conduct video conferencing, and as a result, enable clinicians to make decisions remotely [30]. The health worker is at hand to scrutinize the signs and symptoms that the patient is showing thus enhancing the patient-clinician relationship.

It also expands the possibilities of diagnosis that are not on a hospital basis, but instead promote patient involvement wherein the latter can have a much larger share of the process of managing the heart health [10]. Value-based care will also be supported through such integration in low-resource settings. The AI-supported systems contribute to saving unneeded hospital visits, early intervention, and economically reasonable provision of proactive health care thereby enhancing geography and economics in cardiovascular care [26].

4.6 Open Research Challenges

Indeed, integrating Edge AI with wearable cardiovascular monitoring devices presents several critical challenges, directly stemming from the limitations identified in the reviewed studies. First, there is a challenge of optimizing AI models for edge devices, particularly when it comes to dealing with the complexity and high dimensionality of ECG waveforms. Many of the reviewed studies adopt lightweight or simplified models, such as shallow CNNs or unspecified ML approaches, to cope with hardware and energy constraints, often without systematically reporting how these simplifications will affect diagnostic accuracy. While approaches such as TinyML aim to reduce power consumption, the reviewed literature further shows an unresolved power-accuracy trade-off that could well compromise reliability in real-time monitoring using battery-powered wearables.

The lack of standardized benchmarking datasets and evaluation frameworks is another major limitation. Most studies rely on either proprietary datasets, small cohorts, or simulation-based environments for performance evaluation, which prevents cross-study comparison in most cases. The general lack of widely accepted protocols for the validation and real-world testing of Edge AI–based healthcare devices makes it unclear which systems can meet clinical performance requirements under real-world conditions, due to a lack of generalizability and clinical translation of the findings [18].

Finally, user compliance and long-term wearability of the system also appear as one of the underexplored issues in the literature. Although many studies have demonstrated good performance in terms of algorithms and technology, very few studies have addressed the issues related to user discomfort and the consequent early termination of wearable systems. It again raises a point about the need for patient-centric co-design of Edge AI-supported systems in healthcare, taking into account the principles of behavioral science to address user compliance and wearability of the system in the context of cardiovascular monitoring.

To summarize, it is therefore critically important that these limitations, i.e., model optimization under constrained resources, standardization validation, and consideration of user-centered design, be addressed to ensure the successful transfer of Edge AI-based wearable cardiovascular monitoring systems, so that they can be useful healthcare solutions.

4.7 Recommendations

The integration of Edge AI into wearable cardiovascular devices should be able to revolutionize cardiac healthcare, but many challenges must be overcome for successful deployment. Model optimization of such Edge devices is very important for their effective application in processing ECG waveform data with the least power consumption. Advances in TinyML and beyond model compression techniques are necessary to prepare wearable devices for long periods of operation relative to accuracy and latency [31].

There is also another major obstacle that lacks standardized frameworks in evaluating performance measures of Edge AI healthcare devices. Data development, as well as implementing common validation datasets, would offer better comparability across studies and clear understanding regarding device efficacy in various settings, support broader clinical adoption through measurable and reproducible results [32].

This is very important concerning abandonment of wearables besides alert fatigue, that is, keeping engagement with wearable devices alive. This means the need to apply behavioral science in designing comfortable, easy-to-use devices that also have personalized alerts to improve patient compliance. Another patient-centric co-design to encourage the fact that wearables are functional will thus promote engaging the patients to use them for long periods [33,34].

Lastly, privacy-preserving technologies like Federated Learning or Homomorphic Encryption should always be explored for the safeguarding of sensitive health data. In overcoming these challenges, Edge AI wearables can develop into real-time cardiovascular monitoring devices with precise diagnoses, early intervention, and enhanced health for favor patient care.

5. CONCLUSION

This systematic review explored the integration of wearable devices for real-time cardiovascular monitoring with Edge AI and cloud connectivity for arrhythmia detection, heart failure prediction, and tachycardia management. Wearable gadgets powered with Edge AI models, including CNNs and RNNs, offer diagnostic value with high accuracy (85%-98%) and low latency (<100 ms) for real-time on-device monitoring. However, cloud integration enhances the predictive analytics and personalized treatment to allow model retraining and development based on individual patients' data.

Wearable devices which include smartwatches, biosensor patches, and textile-based sensors can provide constant monitoring and considerably enhance patient engagement and comfort. However, optimization is still required for data privacy, accuracy of sensors, and robustness of the models. Federated Learning along with privacy-preserving models has been acknowledged to be paramount to resolving the privacy issue. However, further work is necessary for data security and model efficiency.

While these initiatives have shown immense hope, there are hurdles that hold them back from being widely adopted in resource-limited settings, such as rural areas and within underserviced populations. Some of these, like the Edge-First Models or Delay Tolerant Data Transmission solutions, provide possible paths to overcoming issues arising from limited and accessible infrastructure; however, more work is to be done to achieve interoperation and access between various resources and platforms.

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