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Edge and Federated Learning for ECG-based Wearable Healthcare: A Review of Decentralized AI Approaches

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Abstract: Background: Wearable healthcare devices have revolutionized continuous cardiac monitoring by enabling real-time acquisition of electrocardiogram (ECG) signals outside clinical environments [8]. However, traditional cloud-based machine learning systems face challenges related to latency, privacy, and communication overhead [9]. Edge computing and federated learning have emerged as promising decentralized artificial intelligence (AI) paradigms that allow ECG data processing directly on wearable devices while preserving patient privacy [5], [10], [11]. This paper presents a comprehensive review of edge and federated learning approaches for ECG-based wearable healthcare systems. The review discusses system architectures, machine learning techniques, federated optimization methods, commonly used ECG datasets, and evaluation metrics. In addition, privacy, security, and computational challenges associated with decentralized ECG analytics are examined. Finally, future research directions including TinyML-based ECG analytics, personalized federated models, and multimodal wearable health monitoring are discussed [21], [29]. This review aims to provide researchers and practitioners with a structured overview of the emerging decentralized AI ecosystem for wearable cardiac healthcare.

Keywords: ECG analysis, wearable healthcare, edge computing, federated learning, decentralized AI, cardiovascular monitoring

INTRODUCTION

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide [6]. Continuous monitoring of cardiac activity through electrocardiogram (ECG) signals plays a critical role in early detection of cardiac abnormalities such as arrhythmia, atrial fibrillation, and myocardial infarction [7].

Recent advances in wearable healthcare devices have enabled long-term ECG monitoring outside hospital environments [8]. Smartwatches, wearable patches, and portable ECG monitors allow continuous data collection during daily activities. However, the large volume of physiological data generated by wearable devices creates significant challenges for centralized cloud-based processing.

Traditional cloud-based healthcare architectures suffer from several limitations including high latency, privacy concerns, network bandwidth constraints, and vulnerability to data breaches [9]. These limitations have motivated the development of decentralized artificial intelligence (AI) frameworks for healthcare analytics.

Edge computing allows data processing and machine

learning inference to be performed close to the data source, such as wearable devices or smartphones [10], [16]. This approach reduces communication latency and enables real-time decision making. In parallel, federated learning has emerged as a distributed machine learning paradigm that allows collaborative model training without sharing raw data [11], [27].
The integration of edge computing and federated learning provides a promising solution for privacy-preserving ECG analytics in wearable healthcare systems [5], [22]. In such systems, ECG data remains locally on devices while only model updates are shared with a central aggregator.

This paper presents a comprehensive review of decentralized AI approaches for ECG-based wearable healthcare. The contributions of this review include:

• A systematic overview of edge computing architectures for wearable ECG systems
• A review of federated learning techniques for decentralized ECG analytics
• A comparison of datasets, algorithms, and evaluation metrics used in recent research
• Identification of open challenges and future research opportunities in decentralized ECG intelligence

The remainder of this paper is organized as follows. Section II presents the background concepts of ECG monitoring, edge computing, and federated learning. Section III discusses literature survey. Section IV discusses the architecture of edge-based wearable ECG systems. Section V reviews edge AI techniques for ECG analysis. Section VI presents federated learning approaches for decentralized ECG analytics. Section VII reviews commonly used ECG datasets. Section VIII discusses performance evaluation metrics. Section XI addresses privacy and security considerations. Section X outlines major research challenges and Section XI presents future research directions. Finally, Section XII concludes the paper.

II. Background Concepts

a. ECG Signal and Wearable Monitoring

The electrocardiogram (ECG) is a non-invasive technique used to measure the electrical activity of the heart [7]. A typical ECG waveform consists of several characteristic components including the P wave, QRS complex, and T wave. Wearable ECG devices enable continuous monitoring of cardiac signals in ambulatory settings [8]. These devices are increasingly used for long-term monitoring and early detection of cardiac abnormalities.

b. Machine Learning in ECG Analysis

Machine learning techniques have been widely applied to ECG signal analysis for tasks such as arrhythmia detection, heartbeat classification, and heart rate variability analysis [12]. Traditional approaches rely on handcrafted feature extraction combined with classifiers such as support vector machines and decision trees. Recent advances in deep learning have enabled automatic feature extraction using convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures [13], [15].

c. Edge Computing in Healthcare

Edge computing refers to the deployment of computational resources closer to the data source, reducing dependence on centralized cloud servers [10]. In healthcare applications, edge devices such as smartphones or wearable processors can perform real-time signal processing and AI inference [16].

d. Federated Learning

Federated learning is a distributed machine learning approach that enables multiple devices to collaboratively train a global model without sharing raw data [11]. Each device trains a local model using its private data and shares only model parameters or gradients with a central server for aggregation [17].

III. Literature Review

The rapid growth of wearable healthcare technologies has significantly increased interest in intelligent ECG monitoring systems [8]. Recent research has focused on integrating artificial intelligence techniques with wearable sensors to enable automated detection of cardiac abnormalities [13], [15]. In particular, the emergence of edge computing and federated learning has opened new possibilities for decentralized ECG analysis while preserving patient privacy and reducing communication latency [10], [11], [22].
To analyze recent developments in this domain, a systematic literature review was conducted focusing on research related to ECG signal analysis, wearable healthcare systems, edge computing, and federated learning. The objective of this review is to identify current trends, technological advancements, and research gaps in decentralized AI approaches for wearable ECG monitoring.

The literature search was performed using major scientific databases including IEEE Xplore, ScienceDirect, SpringerLink, PubMed, and Google Scholar. The search process considered publications between 2018 and 2024, as these years represent the most active period for research in edge intelligence and federated learning applied to healthcare systems [16].

Several keywords and combinations of keywords were used during the search process, including ECG classification, wearable ECG monitoring, edge computing in healthcare, federated learning in healthcare, decentralized AI, and edge AI for biomedical signals. The search results initially returned a large number of publications. These papers were then filtered using predefined inclusion and exclusion criteria.
The inclusion criteria consisted of studies that focused

on ECG signal analysis, wearable healthcare systems, machine learning or deep learning approaches for cardiac monitoring, and decentralized architectures involving edge computing or federated learning [18], [22]. Only peer-reviewed journal articles and conference papers were considered. Studies published between 2018 and 2024 were included to ensure that the review reflects the most recent technological advancements.

The exclusion criteria included papers unrelated to ECG analysis, studies that focused solely on centralized cloud-based machine learning systems, non-peer-reviewed publications, and papers lacking experimental validation or performance evaluation.
After applying these criteria, a set of representative research papers was selected for detailed analysis. The reviewed literature indicates that early research primarily focused on centralized deep learning approaches for ECG classification [13], [14]. However, with the increasing adoption of wearable healthcare devices and the growing importance of data privacy, recent studies have shifted toward edge-based processing and federated learning frameworks [18], [22].

Edge computing enables ECG signal preprocessing and machine learning inference to be performed directly on wearable devices or nearby edge nodes, thereby reducing latency and network bandwidth requirements [10], [18]. This approach is particularly important for real-time cardiac monitoring applications where rapid detection of abnormalities is critical.
Federated learning provides a collaborative learning framework in which multiple devices or institutions can train a shared global model without exchanging raw patient data [11], [22]. Instead, model parameters or gradients are shared and aggregated, ensuring improved data privacy and regulatory compliance [27].
The integration of edge computing with federated learning has emerged as a promising architecture for decentralized healthcare intelligence [10], [22]. In such systems, ECG signals are locally processed on wearable devices or smartphones, while federated learning enables collaborative model improvement across multiple users.

Despite the significant progress reported in recent studies, several challenges remain. These include limited computational resources on wearable devices, heterogeneous data distributions across patients, communication overhead in federated learning systems, and potential security vulnerabilities such as model poisoning attacks [28]. Addressing these challenges is essential for the large-scale deployment of decentralized AI-based healthcare monitoring systems.

Table 1: Summary of Key Research Works in Edge and Federated ECG Analytics

Year	Authors	Method	Dataset	Key Contribution
2019	Rajpurkar et al.	Deep CNN	PhysioNet	Cardiologist-level arrhythmia detection
2020	Xu et al.	Edge-based CNN	MIT-BIH Arrhythmia	Real-time ECG classification on embedded devices
2020	Li et al.	Federated learning framework	Wearable ECG dataset	Privacy-preserving collaborative ECG training
2020	Rieke et al.	Federated learning	Multi-institution datasets	Distributed healthcare AI framework
2021	Islam et al.	Lightweight CNN	MIT-BIH dataset	Energy-efficient arrhythmia detection
2022	Nguyen et al.	Deep learning ECG classification	PTB ECG dataset	Improved ECG classification performance
2022	Chen et al.	Federated deep learning	PhysioNet database	Decentralized arrhythmia detection
2023	Zhang et al.	TinyML ECG classifier	MIT-BIH dataset	On-device ECG classification

2024	Wang et al.	Personalized federated learning	PTB dataset	Personalized ECG classification models

IV. Architecture of Edge-Based Wearable ECG Systems

A typical decentralized ECG monitoring system based on edge computing and federated learning consists of multiple interconnected layers that collectively enable continuous cardiac monitoring, efficient data processing, and privacy-preserving analytics [10], [22]. These layers work together to ensure that ECG signals captured from wearable devices can be analyzed in real time while minimizing dependence on centralized cloud infrastructure.

The first layer consists of wearable ECG sensors, which are responsible for continuously acquiring the electrical activity of the heart [8]. These sensors are commonly integrated into wearable devices such as smartwatches, chest straps, adhesive patches, or portable ECG monitors. Modern wearable sensors are designed to be lightweight and energy-efficient while maintaining sufficient signal quality for medical analysis. At this stage, basic preprocessing operations such as signal amplification, analog-to-digital conversion, and initial noise filtering may be performed to improve the quality of the acquired ECG signals.

The second layer includes edge devices, typically smartphones, tablets, or embedded processors connected to the wearable sensors. These devices serve as local computational units capable of executing artificial intelligence models for real-time ECG analysis [16], [18]. Edge devices perform tasks such as signal preprocessing, feature extraction, and arrhythmia detection using lightweight machine learning or deep learning algorithms. By processing data locally, edge computing significantly reduces latency and limits the amount of raw data that needs to be transmitted over networks [10].

The third layer consists of edge gateways, which function as intermediate nodes that manage communication between multiple edge devices and higher-level servers. Edge gateways can aggregate processed information from several wearable devices, coordinate device synchronization, and perform additional filtering or data management tasks.

Another important component is the federated learning aggregation server, which coordinates decentralized model training [11]. Instead of collecting raw ECG data, the server receives model updates from participating devices and aggregates them using algorithms such as Federated Averaging (FedAvg) to update a global model [17].

Finally, the healthcare cloud infrastructure provides long-term storage, large-scale analytics, and integration with clinical systems. This layered architecture enables scalable, efficient, and privacy-preserving ECG monitoring suitable for modern wearable healthcare applications [22].

V. Edge AI for ECG Processing

a. ECG Signal Preprocessing

Electrocardiogram (ECG) signals acquired from wearable sensors are frequently affected by various sources of noise and artifacts that can degrade signal quality and affect diagnostic accuracy [7], [12]. Common disturbances include baseline wander, typically caused by respiration or electrode movement; power line interference, usually occurring at 50 or 60 Hz due to electrical equipment; and motion artifacts generated during physical activity. These noise components can significantly distort the ECG waveform, making accurate analysis challenging [12].

To address these issues, edge-based preprocessing techniques are applied directly on wearable or edge devices before further analysis [18]. Traditional digital filtering methods such as high-pass, low-pass, and notch filters are widely used to remove baseline drift and power line noise [12]. In addition, adaptive filtering techniques can dynamically adjust filter parameters based on changing signal conditions. More advanced approaches such as wavelet-based denoising allow multi-resolution analysis of ECG signals, effectively separating noise components from clinically important waveform features [12]. Performing preprocessing at the edge reduces communication overhead and ensures that only high-quality signals are used for subsequent analysis [10], [18].

b. Feature Extraction

Feature extraction plays a crucial role in transforming raw ECG signals into meaningful parameters that can be used for automated diagnosis and monitoring [12]. Important ECG features include heart rate, QRS complex duration, RR intervals, PR intervals, QT intervals, and morphological characteristics of ECG waves such as the amplitude and shape of the P wave, QRS complex, and T wave [7], [12]. These features provide valuable insights into cardiac rhythm and are widely used for detecting arrhythmias and other cardiovascular abnormalities [12], [13].

For edge-based healthcare systems, feature extraction algorithms must be computationally efficient and memory optimized due to the limited processing capability of wearable devices [16]. Techniques such as Pan–Tompkins algorithm for QRS detection, peak detection methods, and time-domain statistical feature extraction are commonly employed [12]. In addition, lightweight signal processing approaches and simplified machine learning techniques are often integrated into edge devices to extract relevant information in real time [18]. Efficient feature extraction at the edge enables faster decision making and reduces the need to transmit large volumes of raw ECG data to remote servers [10], [18].

c. Lightweight Deep Learning Models

Deep learning has demonstrated remarkable performance in ECG classification and arrhythmia detection [13], [15]; however, conventional deep neural networks often require significant computational resources and memory, which limits their deployment on wearable and edge devices [16]. To address this limitation, researchers are increasingly developing lightweight deep learning architectures optimized for edge computing environments [16], [18].

Models such as MobileNet, ShuffleNet, SqueezeNet, and TinyML-based neural networks are specifically designed to reduce computational complexity while maintaining high classification accuracy [20], [21]. These models employ techniques such as depthwise separable convolutions, parameter sharing, and model compression to minimize the number of trainable parameters [20]. Furthermore, optimization techniques including model pruning, quantization, and knowledge distillation can further reduce model size and energy consumption [21]. By deploying lightweight deep learning models on edge devices, it becomes possible to perform real-time ECG classification and anomaly detection directly on wearable platforms, thereby reducing latency, preserving user privacy, and improving the responsiveness of remote healthcare monitoring systems [10], [18].

VI. Federated Learning for ECG Analytics

Federated learning (FL) is an emerging distributed machine learning paradigm that enables decentralized training of ECG classification models across multiple devices or institutions without sharing raw patient data [11], [27]. This approach is particularly suitable for healthcare applications where data privacy, security, and regulatory compliance are critical concerns [5], [27]. Instead of transmitting sensitive ECG signals to a centralized server, federated learning allows model training to occur locally on wearable devices, hospital servers, or edge nodes [22].

The typical federated learning workflow involves several stages. First, a global model is initialized at a central coordinating server [11]. This model is then distributed to participating devices or healthcare institutions, where local training is performed using private ECG datasets. After local training, only model updates or gradients are transmitted back to the server, rather than the raw data itself. The server then aggregates these updates using algorithms such as Federated Averaging (FedAvg) to produce an improved global model [17].

By enabling collaborative model development across distributed data sources, federated learning significantly enhances privacy preservation, reduces data transfer requirements, and facilitates large-scale ECG analytics [22], [27]. This paradigm is particularly valuable for integrating data from multiple hospitals, wearable devices, and remote monitoring systems, ultimately improving the robustness and generalizability of ECG-based diagnostic models [22].

VII. ECG Datasets Used in Research

Several publicly available datasets are widely used in electrocardiogram (ECG) research for developing and evaluating machine learning algorithms [15]. Among the most widely used is the MIT-BIH Arrhythmia Database, which contains annotated ECG recordings commonly used for arrhythmia detection and classification studies [24]. The PTB Diagnostic ECG Database provides high-quality clinical ECG recordings that support research on various cardiac diseases [25]. In addition, the PhysioNet Challenge datasets offer large-scale ECG data collected under different physiological conditions and are frequently used for benchmarking advanced algorithms [26]. More recently, wearable ECG datasets containing long-term ambulatory recordings have gained importance, as they reflect real-world monitoring conditions [8]. These datasets provide well-annotated ECG signals that enable researchers to train, validate, and compare machine learning models for reliable cardiovascular analysis [15].

VIII. Performance Evaluation Metrics

Performance evaluation plays a crucial role in assessing the effectiveness of machine learning models used for ECG classification and arrhythmia detection [15]. Several standard evaluation metrics are widely used to measure the diagnostic performance of ECG analytics systems. Accuracy represents the overall proportion of correctly classified samples among all predictions. Sensitivity, also known as recall or true positive rate, measures the ability of a model to correctly identify abnormal cardiac conditions such as arrhythmias. Specificity evaluates how well the system correctly identifies normal heart rhythms, thereby reducing false alarms. Precision measures the proportion of correctly predicted positive cases among all predicted positives, while the F1-score provides a balanced measure by combining precision and recall into a single metric. Another important metric is the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which evaluates the model's ability to distinguish between different classes across various decision thresholds [15].

For edge-based ECG monitoring systems, additional system-level metrics are also considered. These include latency, which measures the time required to generate predictions; energy consumption, which is critical for battery-powered wearable devices; and memory usage, which determines whether a model can be efficiently deployed on resource-constrained edge platforms [16], [19].

IX. Privacy and Security Considerations

Privacy and security are fundamental concerns in healthcare applications involving sensitive patient data such as ECG signals [9]. Traditional centralized machine learning approaches often require the transfer of large volumes of medical data to cloud servers, which raises concerns related to data privacy, regulatory compliance, and unauthorized access [9]. Federated learning addresses many of these issues by enabling decentralized model training where patient data remains on local devices or institutional servers [11], [27]. Only model parameters or gradient updates are shared with the central server, thereby reducing the risk of direct exposure of personal medical information [11].

However, federated learning systems are still vulnerable to several potential security threats. Model poisoning attacks may occur when malicious participants intentionally manipulate model updates to degrade system performance or introduce bias [28]. Inference attacks, such as model inversion or membership inference, can potentially extract sensitive information from shared model parameters [28]. Additionally, communication vulnerabilities during the exchange of model updates may expose the system to interception or tampering [9]. To mitigate these risks, researchers employ advanced security techniques including secure aggregation protocols, differential privacy mechanisms, homomorphic encryption, and robust authentication methods to ensure the confidentiality and integrity of healthcare data [27].

X. Challenges in Edge-Federated ECG Systems

Despite the promising potential of combining edge computing and federated learning for ECG analytics, several practical challenges remain [10], [22]. One of the primary limitations is the restricted computational capability of wearable devices, which typically have limited processing power, storage capacity, and battery life [8], [16]. Deploying complex deep learning models on such devices requires careful optimization and efficient model design [21]. Another significant challenge is the heterogeneity of devices and data distributions. Wearable sensors from different manufacturers may produce ECG signals with varying quality, sampling rates, and noise characteristics [8]. Additionally, ECG datasets collected from different populations may exhibit non-identical data distributions, which can negatively affect federated learning performance [27].

Communication overhead is another critical concern during federated training, as frequent transmission of model updates between devices and servers can increase network traffic and energy consumption [11], [22]. Moreover, energy constraints in wearable devices may limit continuous model training and inference [19]. Addressing these challenges requires innovative solutions such as model compression techniques, adaptive communication protocols, personalized federated learning strategies, and energy-efficient edge AI architectures [16], [29].

XI. Future Research Directions

Future research in decentralized ECG analytics is expected to explore several promising directions that can further enhance the capabilities of wearable healthcare systems [8], [16]. One emerging area is the use of TinyML-based ECG analytics, where ultra-lightweight machine learning models are designed to run directly on microcontrollers and low-power embedded systems [21]. This approach can enable continuous real-time monitoring with minimal energy consumption. Another important research direction is the development of personalized federated learning models that adapt to individual patient characteristics while still benefiting from collaborative learning across multiple devices or institutions [29].
In addition, explainable artificial intelligence (XAI) is gaining increasing attention in medical applications [30]. Providing interpretable explanations for ECG classification decisions can help clinicians better understand model predictions and improve trust in AI-assisted diagnosis [30]. The integration of multimodal wearable sensors, such as combining ECG with photoplethysmography (PPG), blood oxygen levels, or activity monitoring, may also improve the accuracy and reliability of health monitoring systems [8]. Furthermore, the development of standardized benchmarking frameworks and evaluation protocols will be essential for comparing different algorithms and accelerating the adoption of decentralized AI in clinical practice [15].

CONCLUSION

Edge computing and federated learning are rapidly transforming the landscape of wearable healthcare by enabling privacy-preserving, efficient, and real-time analysis of physiological signals such as electrocardiograms (ECG). By shifting computation closer to data sources, edge computing allows ECG signals to be processed directly on wearable devices or nearby edge nodes, thereby reducing latency and minimizing dependence on centralized cloud infrastructure. Federated learning further enhances this paradigm by enabling collaborative model training across multiple devices and healthcare institutions without requiring the exchange of sensitive patient data. This decentralized approach significantly improves data privacy while still allowing the development of robust and generalized machine learning models.

This paper reviewed the current state of decentralized artificial intelligence approaches for ECG-based wearable healthcare systems. Key aspects discussed include edge-based ECG signal preprocessing, feature extraction methods, lightweight deep learning models, federated learning frameworks, publicly available ECG datasets, and performance evaluation metrics. Additionally, important considerations related to privacy protection, system security, and implementation challenges were examined to highlight the complexities involved in deploying decentralized healthcare analytics in real-world environments.

Despite the promising advancements in this field, several challenges remain. Issues such as device heterogeneity, limited computational resources, energy efficiency constraints, communication overhead, and potential security vulnerabilities must be carefully addressed to ensure reliable and scalable deployment. Continued interdisciplinary research in edge intelligence, federated learning algorithms, and secure healthcare data management will be essential for overcoming these challenges. Ultimately, decentralized AI technologies are expected to play a vital role in enabling scalable, intelligent, and privacy-aware healthcare systems, supporting the future vision of smart and connected healthcare ecosystems.

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