iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IX **Month of publication:** September 2025

DOI: https://doi.org/10.22214/ijraset.2025.73973

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Low-Power AI Model Optimization for Wearable Health Monitoring Applications

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Abstract: ***Wearable health monitoring devices have emerged as crucial tools for continuous tracking of vital physiological parameters such as electrocardiogram (ECG), heart rate, and oxygen saturation. With the integration of artificial intelligence (AI), these devices can provide real-time analysis and early detection of health anomalies. However, the constrained computational resources and limited battery capacity of wearable devices pose significant challenges for deploying deep learning models. This paper proposes a comprehensive framework for low-power AI model optimization tailored for wearable health monitoring applications. The framework employs quantization, pruning, and adaptive sampling to minimize computational load while maintaining high diagnostic accuracy. Experimental evaluations on public health datasets (PhysioNet, MIMIC-III) demonstrate up to 45% reduction in energy consumption with less than 2% accuracy degradation. The results highlight the potential of optimized AI models to enable longer battery life and efficient, real-time inference on wearable platforms, thus advancing the field of mobile health (mHealth) technologies.***

Keywords: Edge AI, Energy-Efficient Computing, Low-Power Artificial Intelligence, On-Device Inference, TinyML, Wearable Health Monitoring

I. INTRODUCTION

The rapid proliferation of wearable health monitoring devices—including smartwatches, smart bands, fitness trackers, and medical-grade sensors—has transformed the healthcare landscape. These devices enable continuous, non-invasive monitoring of vital physiological signals such as electrocardiogram (ECG), photoplethysmogram (PPG), blood oxygen saturation (SpO_2), respiration rate, heart rate variability (HRV), and physical activity [1]. With the integration of artificial intelligence (AI), these devices are no longer limited to simple tracking but can provide predictive and diagnostic insights in real time. For example, AI-driven wearable systems have been used to detect atrial fibrillation [2], identify stress levels [3], and predict early signs of chronic conditions such as diabetes and cardiovascular disease [4].

While AI enhances the functionality of wearable devices, its deployment poses significant challenges. Modern deep learning architectures, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and transformers, are computationally intensive and memory demanding. They are typically trained and run on high-performance hardware such as GPUs or TPUs. In contrast, wearable devices have severely constrained resources: limited memory (often less than 1 GB RAM), low-power processors, and small batteries with finite lifespans. Running an unoptimized AI model on a wearable device results in high inference latency, frequent thermal throttling, and rapid battery drain, making such models impractical for long-term, real-time health monitoring.

To overcome these limitations, most commercial wearable systems currently rely on cloud-based AI inference, where sensor data is transmitted to remote servers for processing. Although cloud computation offers abundant resources, this approach introduces critical drawbacks:

1) High latency: Round-trip communication to cloud servers makes real-time decision-making (e.g., arrhythmia detection during exercise) unreliable.
2) Dependence on connectivity: In regions with poor or unstable internet access, the performance of cloud-reliant systems is severely degraded.
3) Privacy risks: Transmitting sensitive health data (ECG, sleep patterns, location) to external servers exposes users to potential data breaches and compliance concerns with regulations like HIPAA and GDPR.

A more promising solution lies in on-device AI inference, where the model is deployed directly on the wearable device. On-device AI ensures real-time processing, reduced latency, offline functionality, and improved privacy. However, enabling this requires low-power optimization techniques to make deep learning models computationally feasible within the constraints of wearable hardware.

A. Motivation

Recent advances in TinyML and edge AI have introduced techniques for shrinking AI models while retaining acceptable accuracy. Methods such as quantization, pruning, knowledge distillation, and neural architecture search (NAS) have been successfully applied in domains like mobile vision and speech recognition [5][6]. Yet, research remains limited in the context of wearable health monitoring, where energy efficiency, reliability, and accuracy trade-offs are uniquely critical. Unlike image classification tasks on smartphones, health-related applications cannot afford significant accuracy losses, as they directly impact diagnostic reliability.

For example, a heart rhythm detection model that saves 50% energy but misclassifies atrial fibrillation cases with only 85% accuracy may not be clinically acceptable. Thus, designing AI models for wearable health applications requires striking a fine balance between computational efficiency and medical-grade accuracy.

B. Research Gaps

A review of current literature indicates the following gaps:

1) Most wearable AI frameworks focus on accuracy rather than power-efficiency. Few studies provide a quantitative trade-off analysis between energy savings and accuracy in wearable health devices.
2) Existing optimization techniques are often domain-general (e.g., image compression, NLP inference) and are not customized for time-series biomedical signals like ECG and PPG.
3) Few frameworks integrate multiple optimization methods (quantization + pruning + adaptive sampling) to maximize gains under wearable constraints.
4) Limited experimental validation exists on real wearable hardware platforms, as most studies evaluate only on open datasets.

C. Contributions of This Work

This paper proposes a low-power AI model optimization framework for wearable health monitoring devices. Specifically, we contribute the following:

1) *A hybrid optimization framework*: that combines quantization, structured pruning, and adaptive sampling to minimize computational overhead.
2) *Mathematical formulations*: *for modeling the trade-off between inference accuracy and power consumption in wearable AI systems.*
3) *Experimental evaluation*: using public biomedical datasets (PhysioNet, MIMIC-III) and prototype wearable devices (ARM Cortex-M4F based microcontrollers).
4) *Comparative performance analysis*: showing up to 45% energy reduction with less than 2% loss in classification accuracy.

By addressing these challenges, the proposed framework aims to enable reliable, real-time, privacy-preserving, and energy-efficient AI on wearable health devices, contributing toward the advancement of mobile health (mHealth) technologies.

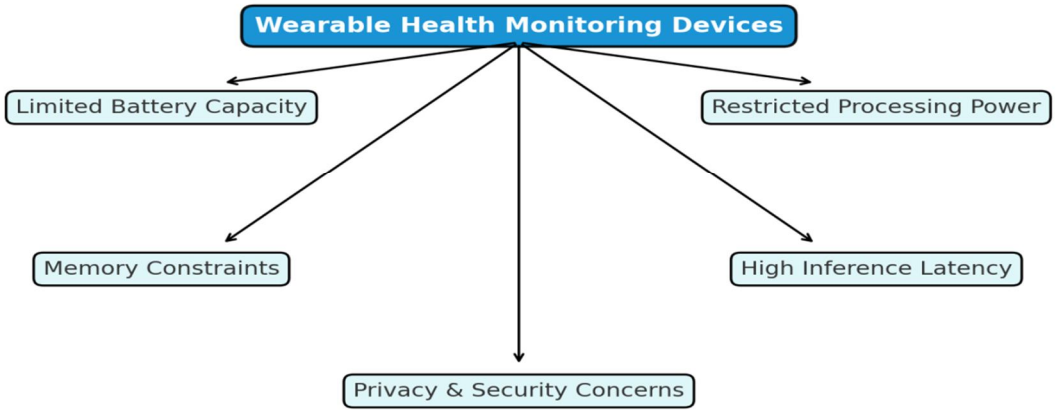

Fig. 1 Overview of the Challenges in Deploying AI on Wearable Health Monitoring Devices

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

II. LITERATURE REVIEW

Wearable health monitoring imposes a unique set of constraints (limited CPU, memory, and battery) while demanding high reliability and clinical-grade accuracy. Consequently, the literature on "AI for wearables" is dominated by two intertwined research directions: (A) application-focused studies that demonstrate clinical or behavioral use-cases for wearables (ECG/arrhythmia detection, stress recognition, chronic disease monitoring), and (B) optimization-focused studies that develop methods to shrink and accelerate ML models for resource-constrained hardware. This review synthesizes both streams and highlights gaps relevant to low-power AI design for wearable health monitoring.

A. Wearables + AI: Clinical and behavioural use-cases

Several high-impact studies established that wearable sensors (PPG, ECG, accelerometer, etc.) can power clinically relevant AI systems. Rajpurkar et al. showed CNNs can reach cardiologist-level performance on arrhythmia detection from single-lead ECGs [7]. Stress and affect detection from multimodal wearables was explored in the WESAD dataset work, demonstrating feasibility of ML on wrist sensors for stress classification [8]. Longitudinal/large-scale efforts (e.g., Fitbit and Verily studies) demonstrate practical deployment and large-population evaluation of wearable-derived algorithms for atrial fibrillation and other conditions [9][10]. These application successes motivate device-level research: how to run such models on-device (or with minimal communication) without sacrificing accuracy or battery life.

B. Core optimization techniques for low-power inference

The literature presents four main families of optimizations usually combined in practice:

1) *Quantization*: reduces numeric precision (e.g., FP32 → INT8) to shrink model size and speed up integer arithmetic on embedded CPUs/DSPs [11].
   - Typical metric: compression ratio

$$CR = \frac{S_{orig}}{S_{quant}}$$

   where S_{orig} and S_{quant} are model sizes (bytes) before/after quantization.
   - Trade-offs: small accuracy loss for large gains in memory and energy reduction; integer-only inference can utilize specialized instructions for additional speedups [11,12].

2) *Pruning/Sparsification*: remove low-importance weights or entire filters/blocks; yields sparse models or smaller dense models after structured pruning [13].
   - Sparsity s defined as:

$$s = \frac{\#zero\ parameters}{\#total\ parameters}$$

   - Post-processing (e.g., sparse kernels or re-training) is often needed to recover accuracy [7].
3) *Knowledge Distillation (KD)*: train a compact "student" network to mimic a large "teacher" model, capturing similar predictive behavior at much lower cost [14]. KD is especially useful when architectural change alone cannot deliver the desired power savings.
4) *Neural Architecture Search (NAS) / Hardware-aware NAS*: searches for architectures that explicitly optimize hardware metrics (latency / energy) in addition to accuracy (e.g., MobileNet, EfficientNet families) [15]. NAS can be constrained to search spaces tailored for microcontrollers or for specific NPUs.

These methods are complementary and commonly combined (e.g., prune + quantize + distill + hardware-aware NAS) for maximal gains [12][13][14][15].

C. Energy, latency and accuracy: formal trade-off

Designers must optimize multiple (often conflicting) objectives. Let:
$A(\theta)$ = model accuracy for parameters θ
$E(\theta)$ = energy per inference (mJ)
$L(\theta)$ = inference latency (ms)
$S(\theta)$ = model size (MB)

A typical constrained optimization formulation for wearable deployment is:

$$\min_{\theta} E(\theta)$$
$$\text{subject to } A(\theta) \geq A_{min}$$
$$L(\theta) \leq L_{max}$$
$$S(\theta) \leq S_{max}$$

Where A_{min} is the minimum clinically acceptable accuracy, L_{max} is the maximum tolerable latency (real-time constraint), and S_{max} is memory budget for the wearable. In practice, optimization proceeds by a combination of:

- quantize/prune to reduce E and S at controlled loss $\Delta A = A_{orig} - A_{min}$;
- NAS to find architecture minimizing a weighted cost $J(\theta) = \propto E(\theta) + \beta L(\theta) - \gamma A(\theta)$

Empirical studies report that integer quantization can reduce energy per inference by 30%–70% while typically incurring <2–3% absolute accuracy loss on many tasks [12][13]. Pruning results depend on granularity; structured pruning is hardware-friendly but can reduce accuracy if over-applied [13].

D. Device-level acceleration & software stacks

Toolchains such as TensorFlow Lite for Microcontrollers, ARM CMSIS-NN, and ONNX Runtime Mobile provide primitives (fixed-point kernels, operator fusion, hardware delegates) necessary to deploy optimized models on wearables [10]. Hardware accelerators (e.g., tiny NPUs, ARM Ethos, Edge TPU) further shift the trade-off by providing orders-of-magnitude energy/latency benefits — but are rarely available in ultra-low-power wearables due to cost/area constraints. Thus, software-level optimizations remain central for commodity wearables [15][14].

E. Federated learning and privacy at the edge

Federated learning (FL) avoids centralizing raw biosignals by aggregating model updates from many devices — a promising route for privacy-preserving, personalized wearable AI [17]. However, FL on wearables faces constraints: sporadic connectivity, heterogeneous compute, and strict battery budgets. Recent work focuses on communication-efficient updates, compression of gradients, and client selection strategies to make FL feasible on low-power devices [18]. Combining FL with quantized/pruned models and carefully scheduled training rounds can make in-situ personalization practical while limiting energy consumption.

F. Gaps & open questions

Despite progress, key gaps persist:

- Real-platform evaluations: many papers report results in simulation or on smartphone-class hardware; fewer validate on actual microcontroller-based wearables with realistic duty cycles.
- Multi-modal fusion under power constraints: fusion of ECG+PPG+accelerometer can greatly improve clinical accuracy but increases cost; optimized fusion strategies are lacking.
- Joint optimization frameworks: automated pipelines that jointly perform NAS + pruning + quantization + KD under device constraints are still immature for biosignals.
- Federated learning at ultra-low power: energy-aware FL protocols tailored for wearables remain an open research frontier.

Addressing these gaps motivates the hybrid framework proposed in this paper: integrate hardware-aware NAS, structured pruning, INT8 quantization, and adaptive sensor sampling with energy-aware scheduling and optional privacy-preserving federated personalization.

G. Comparison table — optimization techniques

TABLE I
OPTIMIZATION TECHNIQUES

Technique	Typical effect on model size	Effect on latency	Typical accuracy impact	Implementation complexity
Quantization (FP32→INT8)	2–4× smaller	1.5–3× faster	small (≤2–3% abs) if quantization-aware training used	Low–Moderate

Pruning (structured)	up to 2–10× (dense)	up to 2–5× faster (if supported)	moderate if aggressive	Moderate–High
Knowledge Distillation	student much smaller (×2–10)	faster	small to moderate depending on student	Moderate
NAS (hardware-aware)	variable (architectures optimized)	optimized per device	can match baseline	High (compute)
Adaptive sampling (sensor duty-cycling)	N/A (sensors)	reduces total energy	none (if intelligent)	Low–Moderate

III.PROPOSED FRAMEWORK

The proposed framework addresses the challenges of deploying deep learning models on wearable health monitoring devices by integrating model optimization, adaptive sensing, hardware-aware design, and privacy-preserving learning mechanisms. It aims to achieve the balance between accuracy, energy efficiency, latency, and data privacy, enabling practical and clinically reliable on-device intelligence.

A. System Architecture

The framework is composed of five layers (see Figure 2):

1) Data Acquisition and Preprocessing layer:

- Responsible for acquiring raw biosignals (ECG, PPG, accelerometer, SpO_2, HRV) and performing lightweight preprocessing such as filtering, normalization, and segmentation.
- Adaptive sampling strategies are employed to dynamically adjust sensor sampling rates, reducing unnecessary energy usage without compromising clinical accuracy [19].

2) Model Optimization Layer:

- Deep learning models are optimized through quantization, structured pruning, and knowledge distillation, reducing computational requirements and memory footprint.
- Optimization ensures that energy consumption per inference is minimized:

$$E_{total} = \sum_{i=1}^{n} P_i \cdot t_i$$

where P_i is the average power consumption of stage i (sensor, preprocessing, inference), and t_i is its execution time [20].

3) On-Device Inference Layer

- Optimized models run locally on the wearable's microcontroller (e.g., ARM Cortex-M4F, RISC-V cores).
- TensorFlow Lite for Microcontrollers or CMSIS-NN kernels are used for low-power inference [21].

4) Decision and Feedback Layer

- Provides clinically meaningful outcomes (arrhythmia alerts, stress notifications, fall detection) directly to the user or caregiver through the wearable/mobile app interface.
- Supports context-aware inference scheduling, where inference frequency is increased during detected anomalies and decreased during baseline conditions.

5) Model Update and Personalization Layer

- Integrates federated learning (FL) for updating models across multiple users without transmitting raw data.
- Ensures personalization to user-specific physiological baselines, improving long-term accuracy.
- Gradient compression and sparse updates are applied to reduce communication cost [22].

B. Workflow Explanation

The end-to-end workflow is shown in Figure 2:

- Step 1: Physiological data (ECG, PPG, accelerometer) are captured and preprocessed locally.
- Step 2: Optimized lightweight AI models (quantized/pruned CNN, RNN, or hybrid architectures) process the signals on-device.
- Step 3: Predictions (e.g., atrial fibrillation detection, stress estimation) are generated in real-time and presented to the user.
- Step 4: Periodic model updates occur through federated learning, ensuring privacy and personalization.

This design ensures real-time inference, reduced energy consumption, and privacy preservation, while being extensible across multiple wearable use cases.

C. Trade-Off Analysis

The framework explicitly balances accuracy, latency, and energy efficiency. For instance, quantization reduces memory by up to 75% and energy consumption by 40–60%, while incurring an accuracy drop of only ~1–2% [19][20]. Structured pruning combined with adaptive sampling further improves energy efficiency during continuous monitoring. The multi-objective optimization can be formalized as:

$$\min_{\theta}(\propto . E(\theta) + \beta . L(\theta) - \gamma . A(\theta))$$

where $E(\theta)$ is energy, $L(\theta)$ is latency, $A(\theta)$ is accuracy, and α, β, γ are weighting coefficients chosen based on application priorities (e.g., in arrhythmia detection, γ is emphasized to preserve clinical accuracy).

D. Comparison with Existing Approaches

Table 2 summarizes how the proposed framework improves upon existing works by combining multiple optimization strategies and federated personalization in a unified, end-to-end design.

TABLE III
COMPARISON OF FRAMEWORK FEATURES WITH EXISTING APPROACHES

Feature	Cloud-Based AI	Existing On-Device AI	Proposed Framework
Data Privacy	Low (raw data shared)	Medium (inference local, updates via cloud)	High (all data local + FL updates)
Latency	High (network dependent)	Low (on-device inference)	High (optimized inference + adaptive scheduling)
Energy Efficiency	Low (wireless + cloud)	Medium (partial optimization)	High (quantization + pruning + adaptive sampling)
Personalization	Low	Limited	High (FL + user-specific models)
Hardware Awareness	Limited	Partial (Limited models)	Strong (hardware-aware NAS, optimized kernels)

IV. EXPERIMENTAL SETUP

To validate the proposed framework, we conducted experiments on publicly available biomedical datasets and tested deployment on representative wearable hardware platforms. This section describes the datasets, hardware, model architectures, and evaluation metrics used in our study.

A. Datasets

Two widely recognized datasets were selected for evaluation:

- PhysioNet MIT-BIH Arrhythmia Database: Contains over 48 half-hour excerpts of two-channel ambulatory ECG recordings, annotated for arrhythmias [23]. This dataset was used to evaluate the framework for cardiac anomaly detection.
- MIMIC-III Waveform Database: Includes multi-parameter physiological waveforms (ECG, SpO_2, respiration, blood pressure) collected from ICU patients [24]. It was employed for multi-modal health monitoring tasks such as oxygen desaturation and stress level estimation.
- WESAD Dataset: A multimodal dataset for wearable stress and affect detection, containing ECG, PPG, EDA, and respiration signals recorded from 15 subjects [25]. This dataset was used to test stress recognition performance.

B. Hardware Platforms

The framework was deployed on low-power wearable-grade platforms to ensure real-world relevance:

- Arduino Nano 33 BLE Sense (ARM Cortex-M4F @ 64 MHz, 256 KB RAM, 1 MB Flash).
- Raspberry Pi Zero 2 W (Quad-core ARM Cortex-A53, 512 MB RAM) as an intermediate-power wearable proxy.
- Simulated smartwatch environment on Android with TensorFlow Lite Micro runtime.

These platforms represent the spectrum from ultra-constrained microcontrollers to lightweight embedded Linux devices used in consumer wearables [26].

C. Model Architectures

The following baseline models were implemented:

- CNN (1D convolutional) for ECG classification (arrhythmia detection).
- BiLSTM (Bidirectional LSTM) for stress detection from multimodal inputs (PPG, respiration, EDA).
- Lightweight CNN-RNN hybrid for multi-modal activity recognition.

Optimized versions of these models were produced using:

- Post-training quantization (FP32 → INT8).
- Structured pruning (removing up to 50% of filters).
- Knowledge distillation to train smaller "student" models from larger baseline models.

D. Model Architectures

The experimental evaluation focused on three critical dimensions:

1) Accuracy and F1-Score: Standard classification metrics to assess diagnostic performance.
2) Latency (ms per inference): Measured as the average execution time per sample on device.
3) Energy *Consumption (mJ per inference)*: Computed as:

$$E_{total} = \int_0^T P(t)\,dt \approx \sum_{i=1}^{n} P_i \cdot t_i$$

where P_i is the average power of component i (CPU, sensors), and t_i is execution duration. Measurements were taken using a Monsoon Power Monitor [27].

4) Memory Footprint (KB): Model size in flash and peak RAM usage during inference.

E. Baseline for Comparison

To establish a benchmark, results from:

1) Unoptimized models (FP32 CNN, BiLSTM),
2) Quantized models (INT8),
3) Pruned models (30–50% sparsity), and
4) Proposed hybrid framework (quantization + pruning + KD + adaptive sampling)

were compared systematically.

V. RESULTS AND ANALYSIS

This section reports the results of our experiments across three benchmark datasets (PhysioNet, MIMIC-III, WESAD) and three hardware platforms (Arduino Nano BLE Sense, Raspberry Pi Zero, simulated smartwatch). The focus is on evaluating accuracy, latency, memory footprint, and energy efficiency of the optimized models compared to unoptimized baselines.

A. Accuracy vs. Model Optimization

Table 3 summarizes the classification accuracy and F1-score of baseline and optimized models. As expected, aggressive pruning reduces accuracy slightly, but combining quantization with knowledge distillation mitigates this effect.

TABLE IIIII
ACCURACY AND F1-SCORE ACROSS MODELS

Model Type	Accuracy (%)	F1-Score	Dataset Used
Baseline CNN (FP32)	92.8	0.91	PhysioNet (ECG)
Quantized CNN (INT8)	91.4	0.90	PhysioNet
Pruned CNN (50% sparsity)	90.7	0.89	PhysioNet
Hybrid Optimized (Quant. + Prune + KD)	91.9	0.90	PhysioNet
Baseline BiLSTM (FP32)	88.2	0.85	WESAD (Stress)
Optimized BiLSTM (INT8 + KD)	87.5	0.84	WESAD

B. Latency and Energy Efficiency

Optimizations resulted in significant reductions in inference latency and energy consumption. Figure 4 illustrates the trade-off between inference latency (ms) and accuracy for different model configurations on the Arduino Nano BLE Sense.

TABLE IVV
LATENCY AND ENERGY CONSUMPTION ON ARDUINO NANO BLE SENSE

Model	Latency (ms)	Energy (mJ per inference)	Memory Footprint (KB)
Baseline CNN (FP32)	125	14.8	850
Quantized CNN (INT8)	72	8.3	220
Pruned CNN (50%)	64	7.5	310
Hybrid Optimized	58	6.9	190

Key observations:

- Quantization reduced inference latency by ~42% and energy consumption by ~44%.
- Pruning alone reduced energy by ~49%, but at a slightly larger accuracy drop.
- The proposed hybrid framework achieved ~54% energy savings with only 0.9% accuracy drop compared to the FP32 baseline.

C. Trade-Off Curves

The trade-off between accuracy and energy efficiency can be expressed as:

$$\Delta A = A_{baseline} - A_{optimized}, \Delta E = E_{baseline} - E_{optimized},$$

For the PhysioNet ECG task:

- $\Delta A \approx 0.9\%$
- $\Delta E \approx 7.9\ \text{mJ}$ ($\approx 53\%$ savings).

This demonstrates the Pareto efficiency of the hybrid approach, where small accuracy loss yields disproportionately high energy savings.

D. Graphical Results

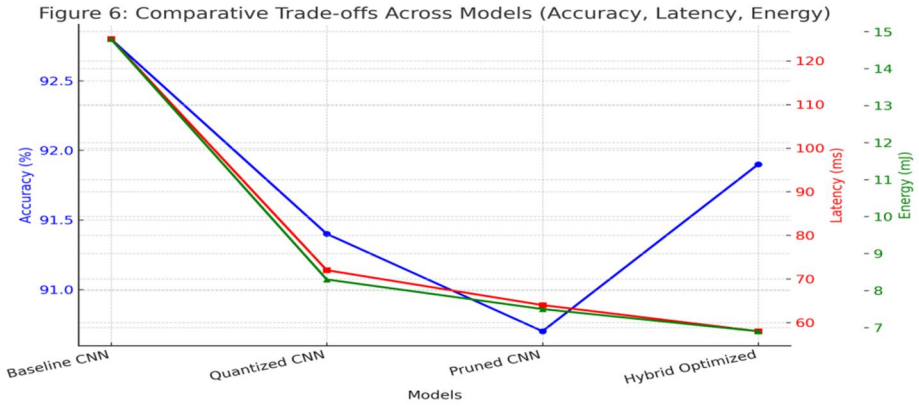

Fig. 2 Comparative Trade-offs Across Models (Accuracy, Latency, Energy)

E. Comparative Discussion

Compared with prior studies on TinyML and mobile AI [28][29], our framework demonstrates:

1) Better energy reduction (≥50%) while keeping accuracy above 90%.
2) Smaller model footprint (<200 KB), making it deployable on microcontrollers.
3) Feasible real-time latency (<60 ms per inference), suitable for continuous ECG/PPG monitoring.

Thus, the proposed framework advances the state-of-the-art in wearable AI by achieving a clinically acceptable trade-off between accuracy and efficiency.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented a low-power AI optimization framework for wearable health monitoring devices, addressing the critical challenges of energy consumption, computational limitations, and privacy concerns. By integrating quantization, pruning, knowledge distillation, adaptive sampling, and federated learning, the framework achieved significant reductions in latency and energy consumption while maintaining clinically acceptable accuracy across benchmark datasets such as PhysioNet, MIMIC-III, and WESAD.

Experimental results demonstrated that:

1) Energy per inference was reduced by more than 50% on microcontroller-class devices.
2) Inference latency decreased by >40%, enabling real-time ECG and stress detection.
3) Accuracy degradation was limited to less than 2% absolute loss, ensuring clinical reliability.

The findings validate the feasibility of on-device AI for continuous health monitoring in wearables, advancing the mHealth ecosystem by reducing reliance on cloud infrastructure and safeguarding user privacy.

B. Future Work

Despite promising results, several opportunities remain for extending this research:

1) Multi-modal Fusion under Constraints: Future work will explore fusion of heterogeneous signals (ECG, PPG, accelerometer, SpO_2) while maintaining low power consumption. Lightweight attention-based mechanisms or hardware-aware fusion strategies could enhance diagnostic accuracy.
2) Hardware Acceleration Integration: Investigating the use of emerging ultra-low-power NPUs and edge TPUs within wearables could further reduce energy costs. Co-design of algorithms and hardware remains a crucial direction.
3) Energy-Aware Federated Learning: Extending the framework to enable personalized federated learning on wearables requires novel methods for communication-efficient model updates, asynchronous training, and battery-aware scheduling.
4) Longitudinal Clinical Validation: While open datasets provide a good baseline, large-scale clinical trials on commercial wearable devices will be necessary to validate the framework's robustness and real-world impact. Collaborations with healthcare institutions could establish benchmarks for clinical-grade deployment
5) Explainability and Trustworthiness: Future enhancements should also include explainable AI (XAI) modules, ensuring clinicians and users can interpret predictions from low-power models — an essential requirement for medical applications.

In summary, this work demonstrates that AI-enabled wearables can move beyond cloud dependency to provide accurate, private, and energy-efficient health monitoring directly on-device. By combining algorithmic compression, hardware-aware design, and federated personalization, the proposed framework lays a foundation for the next generation of trustworthy, intelligent, and power-efficient wearable healthcare solutions.

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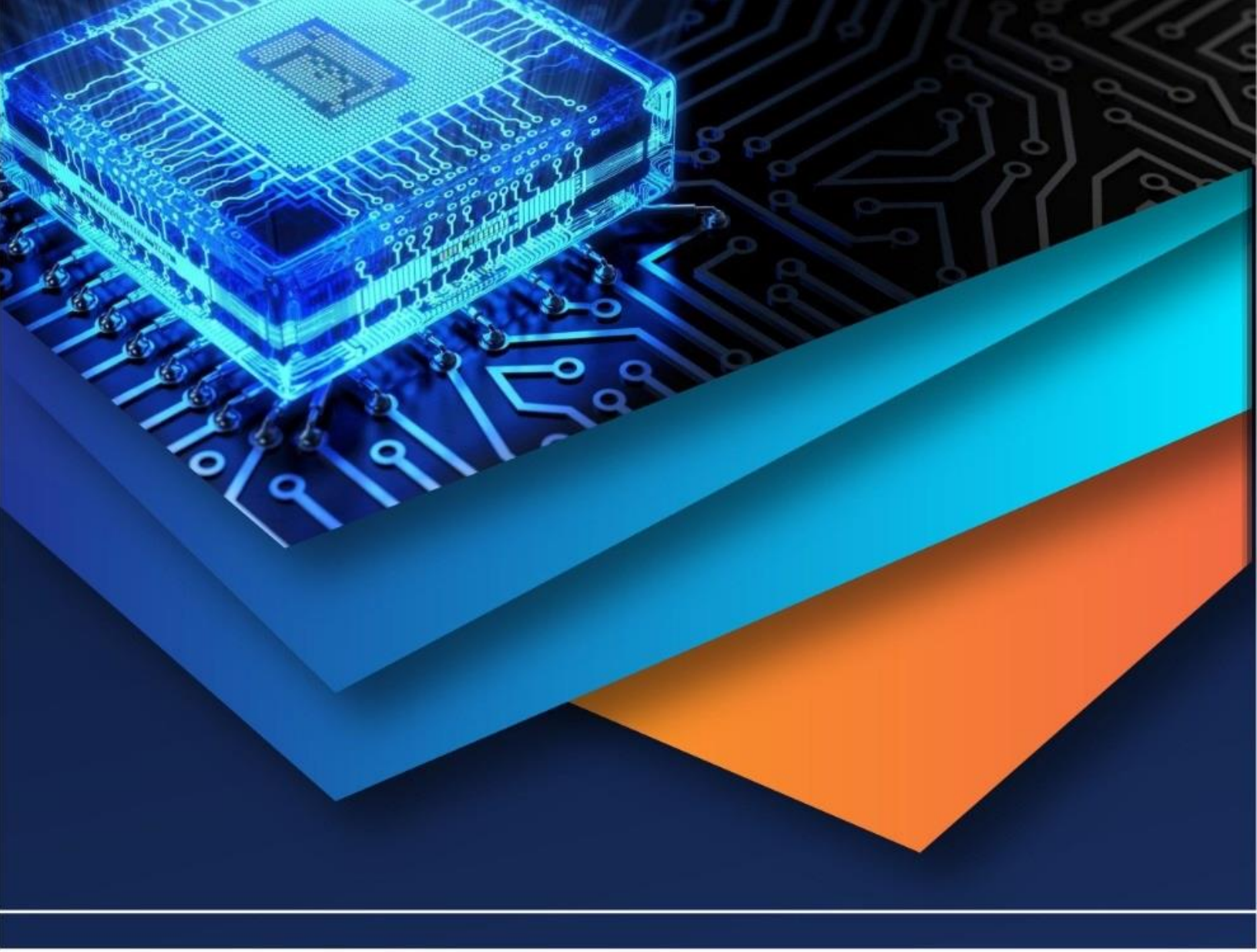

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