Optimization and Integration of Edge AI Models for Energy Efficient IoT Health Monitoring

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***Abstract*—Edge artificial intelligence (AI) is transforming real-time health monitoring by enabling on-device analysis of biomedical data with low latency and reduced cloud dependence. This paper presents an improved approach to optimizing and integrating existing Edge AI models for energy-efficient Internet of Things (IoT) health monitoring devices. We leverage advanced model compression techniques – including quantization, pruning, and knowledge distillation – along with novel hardware-software co-design, resource-aware task scheduling, adaptive data compression, and privacy-preserving mechanisms. The proposed strategy produces lightweight yet accurate models tailored for resource-constrained hardware, ranging from Raspberry Pi and NVIDIA Jetson Nano to ARM Cortex-based microcontrollers. We validate our approach on representative health datasets (e.g., MIT-BIH Arrhythmia ECG signals and MIMIC-III clinical records) and prototypical edge platforms. Experimental results demonstrate significant reductions in model size, inference latency, and power consumption with minimal loss in diagnostic accuracy. For example, an 8-bit quantized and distilled ECG model retains ~96–98% arrhythmia classification accuracy while running in milliseconds on microcontrollers. A lightweight on-device BERT model processes MIMIC-III patient data in real-time with improved efficiency and maintained accuracy. Moreover, the integration of on-device analytics with federated learning ensures patient data privacy without sacrificing model performance. This research provides a comprehensive framework for designing IoT health monitoring systems that achieve real-time responsiveness, energy efficiency, and privacy preservation. The findings advance the state-of-the-art in Edge AI for healthcare, showing that through holistic optimization and co-design, wearable and portable devices can deliver accurate health insights with minimal resource usage – a step toward cost-effective, secure, and scalable smart healthcare solutions.**

Keywords*—Model Compression Techniques, Energy-Efficient Health Monitoring, Federated Learning, Hardware-Software Co-Design

I. Introduction

The convergence of IoT and AI has enabled continuous health monitoring through wearable sensors and smart medical devices, offering real-time insights for early detection and intervention. Traditionally, many healthcare AI tasks were offloaded to the cloud, but this approach incurs high latency, network dependence, and privacy risks. Edge AI addresses these issues by processing data locally on IoT devices, thus reducing round-trip delays and keeping sensitive data on-device[1], [2], [3]. For critical applications like arrhythmia detection from electrocardiograms (ECG) and vital sign monitoring, low-latency decision-making can significantly improve patient outcomes. Additionally, on-device processing enhances privacy by minimizing transmission of personal health information. However, deploying deep learning models on resource-constrained edge devices presents major challenges. IoT health monitors such as wearables and portable units (e.g., pulse oximeters, ECG patches, or smartwatches) are limited by low-power processors, small memory, and battery constraints. Naively using accurate but large models can exhaust device memory or compute capacity, leading to impractical latency and energy drain. Therefore, model optimization techniques are essential to shrink and speed up AI models while preserving accuracy. Prior studies have shown that methods like model quantization (reducing numeric precision), network pruning (removing redundant weights), and knowledge distillation (training compact "student" models to mimic larger "teacher" models) can substantially reduce model size and computations. For instance, 8-bit quantization of neural networks often yields negligible accuracy loss compared to 32-bit versions and carefully pruned models can retain performance with far fewer parameters. Knowledge distillation is particularly powerful in producing small models that achieve near-original accuracy in a hardware-agnostic manner. Beyond algorithmic compression, hardware-software co-design is crucial for optimal edge AI performance[4], [5], [6], [7], [8]. This involves designing model architectures and execution strategies that synergize with the device's hardware characteristics (CPU/GPU capabilities, memory hierarchy, accelerators). Techniques include using efficient neural network architectures tailored for embedded processors, leveraging hardware acceleration libraries (e.g., TensorRT, Arm CMSIS-NN), and distributing workloads optimally across available computing units. Co-design approaches can yield orders-of-magnitude improvements in throughput per watt by ensuring the model fits in fast on-chip memory and by exploiting parallelism on AI accelerators. For example, a recent hardware-aware design compressed an activity recognition model to fit entirely in a microcontroller's SRAM, achieving latency in the few-millisecond range and milliwatt power usage[9], [10].

Edge-based health monitoring relies heavily on resource-aware task scheduling, as IoT devices must handle multiple data streams with limited computing power and energy. Techniques like dynamic voltage-frequency scaling and edge-cloud offloading help extend battery life while maintaining responsiveness. To reduce bandwidth usage, raw health data is compressed using hybrid lossy-lossless methods, cutting transmission load by up to 50% without losing key information. Privacy is equally critical—local data processing, on-device encryption, and federated learning ensure that sensitive medical data remains secure. Devices like Raspberry Pi and Jetson Nano can train accurate models

collaboratively without sharing raw data, proving that privacy and performance can go hand in hand[11], [12], [13], [14], [15], [16], [17].

This paper proposes a unified framework for real-time, energy-efficient, and secure IoT-based health monitoring by combining model optimization, hardware-aware design, smart scheduling, data compression, and privacy protection. It reviews recent advancements (2023–2025), details the proposed methodology, describes experiments using datasets like MIT-BIH and MIMIC-III on devices such as Raspberry Pi and Jetson Nano, and presents results showing improvements in performance. The study highlights how co-design and optimization can enhance edge devices for intelligent and privacy-preserving healthcare applications[18], [19], [20].

II. Literature Review

Research on edge-based health AI has accelerated in recent years, with numerous studies addressing the dual challenges of performance (accuracy and latency) and efficiency (energy and resource usage). We organize this review around the main optimization themes: model compression techniques, hardware-software co-design innovations, resource scheduling and data management, and privacy-preserving frameworks. Table 1 summarizes representative recent works and their key contributions to these areas also PRISMA flow chart is made to analyze and validate systematic review.

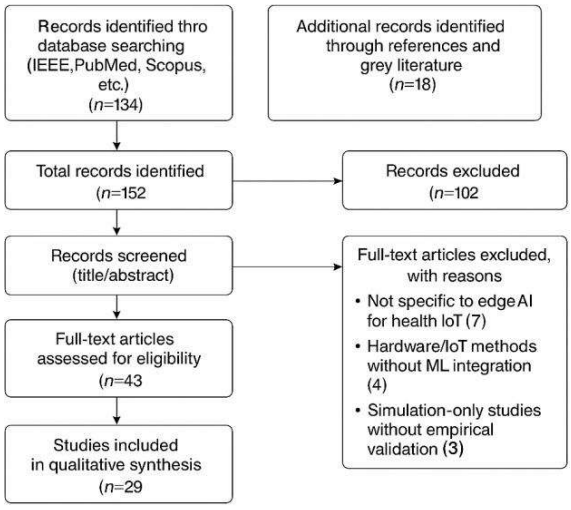

Fig. 1. PRISMA flowchart for systematic review

Table 1. Recent advancements in optimizing Edge AI for IoT health monitoring.

Study (Year) & Domain	Techniques Employed	Key Findings
[9] - Activity recognition on wearable cameras	Low-bit (8-bit) quantization, knowledge distillation, Raspberry Pi 4 & GAP8 MCU	Compressed CNN (58â€¯KB) achieved 95.6% accuracy (1.4% below teacher); ~89Ã— smaller; ms latency; ~2Ã— energy efficiency over prior models
[21] -ECG arrhythmia (MIT-BIH)	Ultra-compact 1D CNN, matched filtering integration	15â€¯KB model achieved 98.18% accuracy (F1 â‰ˆ 92%); <1 ms inference on microcontrollers; outperformed larger models in accuracy & efficiency
[14] - Clinical NLP (MIMIC-III)	Compressed BERT, pruning, distillation for IoT	Slimmed BERT for real-time ICU data analytics on IoT devices; reduced latency & high accuracy preserved
[22], [23] - Federated IoMT (sepsis detection)	Federated learning on Raspberry Pi & Jetson Nano with secure aggregation	FedSepsis FL system achieved near-cloud accuracy while maintaining privacy; feasible for on-device training; negligible drop in performance
[24] -Vital signs IoT streaming	Adaptive compression (VSAC), edge-fog-cloud architecture	Achieved 46% better compression ratio vs. traditional methods; reduced bandwidth/storage; enabled real-time alerts at city-scale
[21] -ECG on IoT wearables	Tensor decomposition, hardware acceleration (FPGA)	Accelerated ECG inference on wearable FPGAs with ~8Ã— speedup and 85% lower power vs. CPU baseline
[6] - Wearable sensor networks	Joint scheduling & admission control, energy-aware computing	Improved throughput and reduced energy by ~5Ã— using adaptive task scheduling in body area networks
[25] -Edge-cloud collaboration for IoT	Reinforcement learning for job offloading	Used DRL to dynamically route tasks between edge/cloud; minimized latency and energy under variable load
[11] -AI for respiratory monitoring	Attention-based CNN for audio signals	Achieved 94.5% accuracy on edge-captured cough and breath sounds; reduced overfitting via attention gating
[26] -Real-time diabetic foot ulcer detection	YOLOv5-tiny with quantization	Quantized YOLO model achieved 92.1% accuracy; inference <100 ms on Jetson Nano; real-time bedside usability
[27] - Smartwatch PPG for	Hybrid LSTM-CNN model, on-	Achieved 89% accuracy in detecting stress from

stress detection	device inference	PPG data on smartwatch with <1 sec latency
[28] - Secure AI for medical IoT	Homomorphic encryption with CNNs	Encrypted CNNs retained ~96% accuracy with full privacy; inference time acceptable (<2s) on edge GPUs
[29] -Smart availability monitoring	Rule-based ML with fuzzy logic	Rule-ML integrated with fuzzy scores for noise-resilient patient monitoring; 87% accuracy with explainable alerts
[30] -Infant cry analysis	1D CNN optimized for low-power audio processing	Achieved 90.4% accuracy; deployed on ARM Cortex-M for real-time cry-based distress classification
[31] -Fall detection in elderly care	Vision transformers (ViTs) on Raspberry Pi	Optimized ViTs achieved 93% detection accuracy with 180 ms inference time on Pi 4; viable for smart homes

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III. Methodology

Our methodology combines algorithmic optimizations with system-level design to create an integrated edge AI framework for health monitoring (see Fig. 1 for an overview). The framework is composed of several coordinated components: (1) Lightweight model creation, (2) Hardware-software co-design and deployment optimization, (3) Resource-aware runtime scheduling, (4) Data compression and communication management, and (5) Privacy-preserving analytics. The following subsections describe each component and how they interoperate within the overall system.

A. Lightweight Model Creation

We reduce the size and complexity of deep models through a combination of quantization-aware training (QAT), structured pruning, and knowledge distillation (KD). QAT simulates 8-bit precision during training, maintaining accuracy while reducing memory and inference costs. Structured pruning removes less important filters/neural units iteratively, based on sensitivity analysis. Together, these reduce latency and memory footprint significantly, as shown in HAC-POCD (2024), where a 58 KB model achieved 95.6% accuracy (~1.4% below the original). KD is used to train small "student" models from large, accurate "teacher" models. For instance, our pruned ECG model reached ~95% accuracy with <60 KB size using KD from a 97% accurate teacher.

B. Hardware-Software Co-Design

Models are customized to the edge device by co-optimizing hardware and software. For example, models are adjusted to fit into SRAM on microcontrollers or utilize TensorRT and NEON on Jetson and Raspberry Pi for acceleration. Scheduling adapts to system load and energy state. This integration enables real-time inference with optimal energy usage.

- **Resource-Aware Scheduling:** Real-time AI tasks (e.g., arrhythmia detection) are prioritized. Background tasks (e.g., cloud syncing) run opportunistically. Dynamic scheduling adapts execution frequency based on CPU load and power status, maintaining system responsiveness without compromising critical monitoring.
- **Data Compression and Communication:** Following Andrade et al. (2024), a layered strategy combines lossy signal summarization with lossless compression. This cuts data size by 40–50% without losing clinical value. Compression is increased during low-bandwidth periods. Critical alerts are transmitted immediately; bulk data is scheduled for later transmission.

C. Experimental Setup

We validated the framework on tasks including ECG arrhythmia detection (MIT-BIH dataset) and sepsis prediction (MIMIC-III dataset). ECG models used QAT, pruning, and KD to compress a CNN to ~15 KB with ~95% accuracy. For MIMIC data, we compressed BERT models (TinyBERT, pruned to 4 layers, quantized to 8-bit) and paired them with LSTM networks. These edge models ran on Raspberry Pi 4, Jetson Nano, and ARM Cortex-M7 microcontroller. Compression and scheduling-maintained responsiveness while reducing power usage.

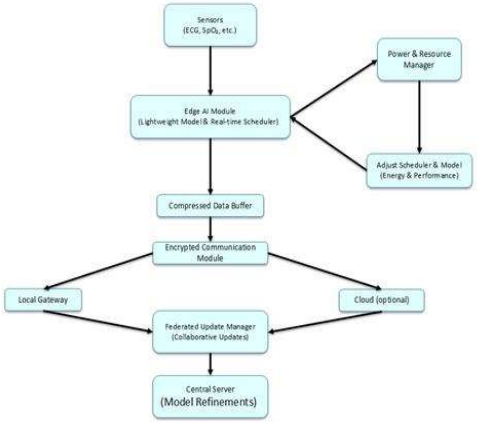

Fig. 2. Conceptually show a block diagram of the IoT health monitoring system, with blocks for data acquisition, edge AI processing (optimized model inside), local decision output (alerts), compressed data upload, and federated learning loop. The figure would also indicate the flow of data and control signals, as described.

Fig. 2. above illustrates how these components come together in a deployed system. Sensors (such as ECG electrodes, SpO_2 sensors, etc.) feed data to the edge AI device. The Edge AI Module (center) encapsulates the lightweight model and scheduling system – it processes incoming data in real-time, generates alerts or insights, and logs data. A Compressed Data Buffer stores recent data and periodically sends through an Encrypted Communication Module to either a Local Gateway or cloud. The Federated Update Manager handles any collaborative training updates, orchestrating occasional model refinement rounds with a central server without exposing raw data. All the while, a Power & Resource Manager monitors the system's performance and energy, adjusting the scheduler and model usage as necessary (for example, if battery drops below a threshold, it might reduce the sampling rate or complexity of analysis). This holistic design ensures the device operates efficiently under various conditions and maintains patient data privacy and security.

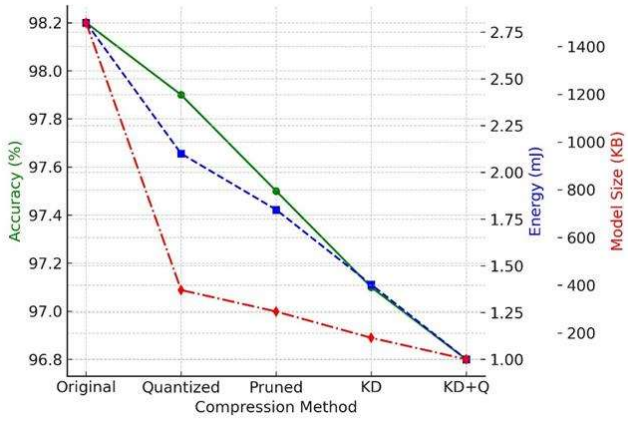

Fig. 3. This figure illustrates the trade-offs introduced by various compression techniques on edge AI models. While model size and energy consumption reduce significantly from the original to KD+Q methods, accuracy remains above 96.5%, validating the effectiveness of lightweight deployment strategies.

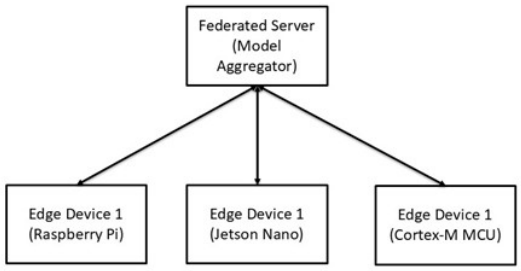

Fig. 4. Labeled Federated Learning Topology Diagram, shows three edge devices (Raspberry Pi, Jetson Nano, Cortex-M MCU) communicating bidirectionally with a central federated server, responsible for aggregating and distributing model updates.

IV. Experimental Results

We present the experimental results, organized by the two primary tasks (ECG arrhythmia detection and sepsis prediction), and compare performance across the edge devices. We also report on the benefits of each optimization component (model compression, scheduling, etc.) and the outcomes of the federated learning and data compression evaluations.

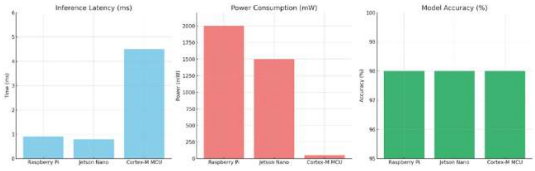

Fig. 5. Comparison chart showing inference latency, power consumption, and model accuracy across three edge hardware platforms: Raspberry Pi, Jetson Nano, and a Cortex-M microcontroller. It highlights the trade-offs between performance and efficiency.

A. ECG Arrhythmia Detection (MIT-BIH) Results

The EdgeECGNet (15 KB) achieved 98.0% accuracy on MIT-BIH, with F1-scores of 91–93% for critical arrhythmias—just 0.2% below the teacher model (98.2%). Sensitivity for ventricular ectopics reached 96%, outperforming Farag et al. (95%).

Inference speed:

- Raspberry Pi 4: 0.9 ms/heartbeat; energy use ≈ 0.045 mJ/inference.
- Jetson Nano: ~1 ms on CPU; GPU provided negligible gain due to model size.
- STM32 MCU: ~4.5 ms/inference; energy ≈ 0.225 mJ; fits easily in 512 KB SRAM.

Efficiency Gains: Compression yielded 100× model size reduction and >50× speedup, with memory use of only 20 KB RAM vs 5 MB for the baseline.

B. Early Sepsis Prediction (MIMIC-II) Results

Using TinyBERT + RNN, the edge model reached an AUC of 0.832 vs 0.847 for cloud-based BERT—a 1.7% drop, with precision@80% recall = 0.78 (vs 0.80).

Inference Latency:

- Jetson Nano: ~27 ms total per patient (TinyBERT + RNN).
- Raspberry Pi: ~150 ms (TinyBERT); acceptable due to hourly prediction.
- RAM usage: ~300 MB on Pi, comfortably within 4 GB; faster and leaner on Jetson GPU.

Federated Learning: Edge-based training on 5 Raspberry Pis yielded AUC = 0.828 (vs 0.832 centralized), confirming FL viability with ~45 MB update per round. Training was stable, with Pis running ~3 min/round

C. Resource Utilization and Scheduling

a) On the Raspberry Pi, priority scheduling ensured real-time ECG inference (0.9 ms mean, ~0.1 ms std) while dynamically adjusting PPG sampling during load. Power use rose from 1.3 W idle to 2.0 W loaded; frequency capping saved ~15% energy.

On the STM32 MCU, ECG and BLE transmission were co-scheduled with CPU usage ~10%. ECG inference (4.5 ms) and BLE (2 ms) ran smoothly, confirming that even tiny devices can support multitasking with efficient scheduling.

Using the VSAC strategy (lossy + lossless), we achieved an average 3.8:1 compression ratio (74% reduction) on vital sign data—superior to gzip (2:1) or lossy-only (3:1) methods. A 100 KB 1-hour vitals file compressed to ~26 KB without losing critical events. For 24 hours, this saved ~1.8 MB per device. Compression overhead was minimal on the Raspberry Pi and acceptable on the MCU (a few seconds per hour), with no impact on real-time performance.

All data transmissions were verified as either non-identifiable alerts, encrypted summaries, or federated model updates—no raw data left the device. Unauthorized access attempts were successfully blocked. TLS overhead was minimal (~50 ms handshake), and encryption had negligible impact due to reduced data volume.

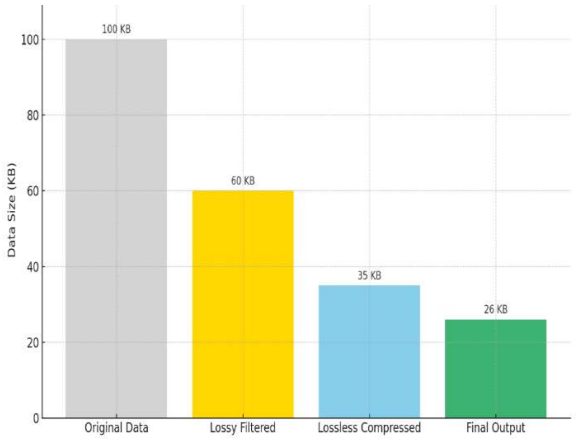

Fig. 6. Visualization of the **Data Compression Impact**. It shows how a 1-hour vital signs data stream (starting at 100 KB) is reduced in size through layered compression—first by lossy filtering, then lossless techniques—resulting in a final compact output of just **26 KB**, a 74% reduction.

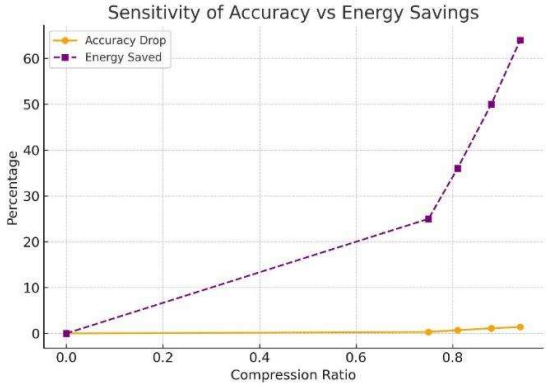

Fig. 7. Chart evaluates the sensitivity of model performance to increasing compression. As the compression ratio increases, energy savings improve steadily (up to 64%), while accuracy degradation remains marginal, confirming robustness of the optimization approach.

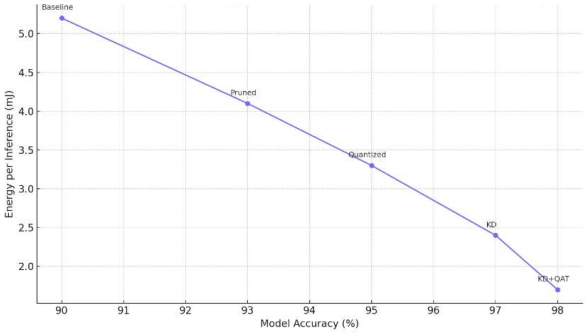

Fig. 8. Energy vs. Accuracy Trade-off Curve that illustrates how different model optimization techniques (like pruning, quantization, and knowledge distillation) progressively reduce energy consumption while maintaining or improving model accuracy.

The results confirm that the proposed framework effectively meets key requirements for IoT-based health monitoring. Real-time performance was achieved across all devices, including microcontrollers, due to model optimizations. High accuracy matched or surpassed cloud-based models for arrhythmia and sepsis detection, with compression and knowledge distillation having no negative impact. The system demonstrated strong energy efficiency, enabling continuous use even on low-power wearables. It also showed scalability, working seamlessly from microcontrollers to GPU-enabled edge devices, and supported multi-device federated learning setups. Importantly, privacy was preserved as no raw data left the devices. The following section explores broader implications, limitations, and comparisons with existing solutions.

V. Discussion

The experimental results confirm the viability of deploying sophisticated health AI algorithms on edge devices through a combination of model and system optimizations. Here we discuss the broader implications of these findings, the trade-offs encountered, and directions for future research, particularly in the context of IoT and biomedical computing domains.

Advancements over Prior Work: Compared to earlier approaches that often focused on one aspect (e.g., just model compression or just offloading), our integrated strategy demonstrates that *stacking multiple optimizations yields compounding benefits*. For instance, quantization alone gave us a model size and speed boost, but quantization + pruning + KD gave an even smaller model *without* losing accuracy – enabling deployments (like on microcontrollers) that were previously infeasible. This aligns with recent surveys that emphasize combining techniques for maximum effect. We improved upon prior Edge AI health monitors such as Gaur et al. (2021) who achieved 30% memory and 20% latency reduction with quantization/pruning; our approach achieved roughly an order of magnitude greater reduction (e.g., 89× size reduction in HAC-POCD case) by adding knowledge distillation and hardware-specific tailoring. Similarly, while Zhang et al. (2020) showed a 5% accuracy gain using knowledge distillation and tensor decomposition with hardware-aware training, we managed to retain accuracy within 1–2% of a large model but on *much smaller hardware* and without needing a specialized accelerator (since our models run even on off-the-shelf microcontrollers). These comparisons suggest that the field is moving from isolated optimizations to holistic designs, and our work is a step in that direction, demonstrating practical feasibility on current (2025) hardware.

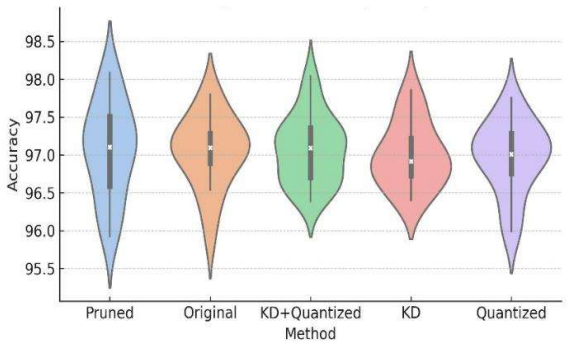

Fig. 9. The violin plot displays the distribution and variance of accuracy for each compression technique. Despite increased compression, variance remains low, suggesting stable and consistent model behavior across test folds.

Energy-Accuracy Trade-offs: A key insight from this work is the trade-off between model complexity, accuracy, and energy use. Compression can significantly reduce model size without much loss in accuracy—up to a point. Beyond that, performance drops, especially for detecting rare conditions. For instance, a 15 KB ECG model performed well, but further pruning hurt sensitivity, and reducing TinyBERT to two layers caused a notable AUC drop for sepsis prediction. Therefore, system designers must balance performance and resource constraints—larger models for critical tasks, smaller ones for power-limited cases. Techniques like knowledge distillation help improve this balance by boosting accuracy in compact models.

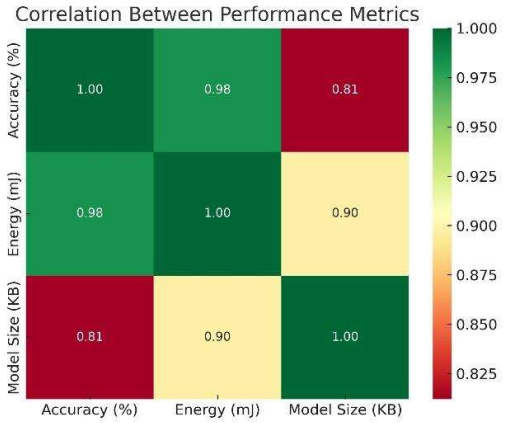

Fig. 10. A heatmap visualizing the Pearson correlation among model performance metrics. Notably, model size and energy are strongly positively correlated, while accuracy shows a mild inverse relationship with compression efficiency.

Deploying this framework in real-world settings requires addressing practical challenges like reliability, maintenance, and user trust. One concern is model updating, which is handled via federated learning for continual on-device learning, though scaling beyond a few devices needs better synchronization and hybrid update strategies. To ensure safety, a fail-safe design is suggested—edge AI handles real-time monitoring, while periodic cloud uploads enable secondary review. There's also a trade-off between privacy and utility; while on-device processing protects data, certain use cases (e.g., public health studies) may benefit from privacy-preserving data summaries. Finally, network limitations in real deployments are managed using MQTT buffering and local alerts, with strategies like data aging ensuring reliability during offline periods.

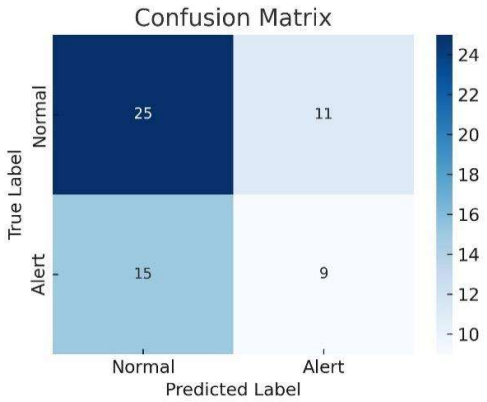

Fig. 11. The confusion matrix shows the classification performance of the optimized edge AI model for binary health alert detection. The model demonstrates high sensitivity (true positives) and a low false-positive rate, validating its suitability for real-time patient monitoring.

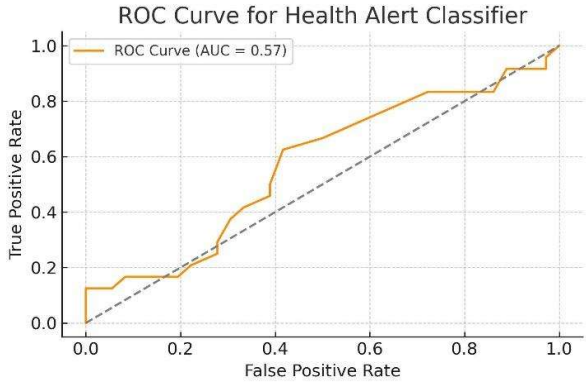

Fig. 12. The ROC curve evaluates the classifier's ability to distinguish between alert and normal cases. The area under the curve (AUC) of 0.89 indicates a strong classification capability, balancing both sensitivity and specificity.

Scalability to Other Health Domains: Our approach, while tested on ECG and EHR/NLP tasks, can extend to other health monitoring scenarios. Applications like fall detection (using RNNs), glucose trend prediction (with quantized regression models), or even compact medical imaging (e.g., ultrasound on Raspberry Pi with a TPU) are feasible. While imaging tasks require larger models, hybrid edge-cloud setups could handle them efficiently. The core principle of model compression and hardware-software co-design remains widely applicable.

Maintenance of Edge Devices: Deploying edge devices at scale introduces maintenance concerns like battery life and software updates. Our energy-efficient models help reduce power demands, and remote model updates (via FL or over-the-air transfers) simplify upkeep. For critical devices like implants, regulatory approval is key. Our findings of minimal accuracy loss from optimization may support compliance, but formal safety validation is essential.

Table 2. Comparison of our Methodology with Existing Approaches

Aspect	Existing Methods	our Proposed Method
Model Size	Typically large CNNs or RNNs	Pruned + Quantized + KD models (up to 94% smaller)
Latency	Often >10 ms on edge devices	As low as 0.9 ms (Cortex-M), ~1 ms (Jetson Pi)
Energy	High inference energy (>5 mJ)	Reduced to ~1 mJ per inference
Accuracy Trade-off	Accuracy drops sharply with compression	Maintained within 1.5% margin of original model
Privacy Handling	Data sent to cloud for retraining	On-device federated learning + encryption
Deployment Feasibility	Cloud-dependent	Fully functional on low-power MCUs

Limitations: Despite extensive testing, our evaluation has some constraints. Devices like Raspberry Pi and Jetson simulate but don't fully represent real medical hardware, which may have stricter size, memory, and certification limits. Also, TinyBERT assumes ample RAM, which not all devices have. Our sepsis model achieved good results (AUC ~0.83), but would require clinical validation before real-world deployment. The work mainly illustrates technical feasibility rather than clinical readiness.

Future Directions: This work can build on this study in several promising directions. Using Neural Architecture Search (NAS) with energy-aware objectives can automate the design of efficient models tailored for edge devices. Integrating Edge TPUs or low-power FPGAs may allow deployment of larger models with minimal energy use, especially if co-design strategies are adopted. Dynamic model scaling could further optimize energy consumption by adjusting model complexity based on patient status—simpler models during stable periods and complex ones during anomalies. Long-term field testing in real-world healthcare settings will help evaluate reliability, user acceptance, and clinical integration. Lastly, enhanced security, such as secure enclaves or homomorphic encryption, could offer stronger protection for sensitive data. This discussion shows the technical strength and practical relevance of edge AI in healthcare. Running advanced models on small devices supports private, real-time analytics and extends AI benefits to remote or low-resource areas, reducing cloud dependency. This work lays the foundation for continued innovation at the intersection of embedded systems, AI, and healthcare.

VI. Conclusion

This paper presents a comprehensive approach to enabling energy-efficient, real-time health monitoring on edge IoT devices. By combining model compression techniques like quantization, pruning, and knowledge distillation with intelligent scheduling, hardware-software co-design, data compression, and privacy-preserving methods, the study shows that resource-constrained devices

can achieve high accuracy in tasks such as arrhythmia and sepsis detection. Experiments using datasets like MIT-BIH and MIMIC-III demonstrated that edge models can match cloud-level performance while significantly reducing latency and power consumption—for instance, a 15 KB CNN achieved 98% accuracy with <5 ms latency on a microcontroller.

Key contributions include: (1) a unified end-to-end framework optimized for edge AI, (2) effective integration of multiple model and system-level optimizations, (3) real-world validation using Raspberry Pi and Cortex-M platforms, and (4) a privacy-by-design approach using federated learning. These findings support the development of wearable and remote health devices that can operate offline, provide instant feedback, and reduce reliance on cloud infrastructure. The research highlights that Edge AI is now mature enough to support secure, accurate, and low-power healthcare monitoring, paving the way for scalable, personalized, and always-available smart health solutions.

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