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TinyML on the Edge: Model Compression, On-Device Learning, and Energy–Latency Trade-Offs

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Abstract

This review article aims to synthesize contemporary developments in Tiny Machine Learning (TinyML)—with emphasis on model compression, on-device learning, and energy–latency trade-offs—to establish an integrated understanding of how intelligent inference and adaptation can be achieved on highly resource-constrained edge devices. This study employed a qualitative systematic review design grounded in thematic analysis. Sixteen peer-reviewed articles published between 2019 and 2025 were selected from major scientific databases, including IEEE Xplore, ACM Digital Library, ScienceDirect, and SpringerLink, based on relevance to TinyML, model compression, and edge inference optimization. Data collection was exclusively literature-based, following theoretical saturation principles. All selected studies were imported into NVivo 14 for open, axial, and selective coding. Analytical procedures involved identifying recurring concepts and grouping them into higher-order themes through iterative interpretation. The reliability of coding was maintained via memo-keeping and cross-verification of emergent categories. Four major thematic categories emerged: (1) Model compression and optimization, encompassing pruning, quantization, distillation, and compiler-level acceleration; (2) On-device learning and adaptation, highlighting federated, meta-learning, and reinforcement learning techniques for autonomous edge model evolution; (3) Energy–latency trade-off management, focusing on multi-objective optimization frameworks, hardware–software co-design, and low-power accelerators; and (4) Application scenarios and benchmarking, demonstrating TinyML's adoption in vision, audio, biomedical, and industrial IoT contexts supported by standardized metrics such as MLPerf Tiny. Collectively, these findings confirm that achieving sustainable edge intelligence requires a unified co-optimization of algorithmic, hardware, and runtime dimensions. TinyML represents a convergence of embedded engineering and artificial intelligence where compression, learning, and energy optimization interlock to enable autonomous, low-power, and responsive systems. Future research should advance adaptive, security-aware, and cross-domain frameworks to realize robust, scalable edge intelligence.

Keywords: Tiny Machine Learning (TinyML); model compression; on-device learning; edge AI; energy–latency optimization; neural architecture search; embedded intelligence.

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1. Introduction

In recent years, the convergence of embedded systems, Internet of Things (IoT), and machine learning has ushered in a transformative paradigm: Tiny Machine Learning (TinyML). Whereas traditional machine learning and deep neural networks often rely on cloud-based training and inference, TinyML seeks to push inference—and increasingly, training—onto severely resource-constrained devices such as microcontrollers, low-power sensors, and edge nodes (Warden, 2018; "Tiny Machine Learning and On-Device Inference: A Survey," 2025). The motivation is clear: executing models directly on the edge reduces communication cost, enhances privacy, lowers latency, and enables responsiveness even under intermittent connectivity (Edge AI: A survey, 2023). However, the constraints posed by memory, compute, energy, and real-time requirements demand new techniques and trade-offs that differ fundamentally from those in conventional cloud or high-end server settings.

TinyML's relevance extends across domains. In smart agriculture, for example, on-device models have been used to predict soil moisture or detect anomalies in sensor streams, reducing the need for continuous cloud connectivity (Tiny Machine Learning and On-Device Inference: A Survey, 2025). In wearable devices and biomedical sensing, TinyML enables continuous monitoring with minimal battery draw. In industrial IoT, embedding intelligence at sensor nodes allows for immediate fault detection and localized adaptation without the round trip to a central server. These wide-ranging applications underscore that TinyML is not only a technical curiosity but a key enabler for pervasive, context-aware intelligence (Advancements in TinyML: Applications, Limitations, and Impact, 2023).

Yet deploying machine learning on microcontrollers or low-power processors is far from trivial. Standard neural networks often require millions of parameters and 32-bit floating-point operations—demands that exceed what is feasible on devices with tens or hundreds of kilobytes of RAM and tight energy budgets. This mismatch has motivated a growing body of work on model compression, lightweight architecture search, hardware–algorithm co-design, dynamic inference, and on-device learning, all in service of achieving practical performance under extreme constraints (A comprehensive review of model compression techniques, 2024; Training Machine Learning Models at the Edge: A Survey, 2024). Alongside these innovations, the question of energy–latency trade-offs emerges as a central governing principle: how much energy can one expend to reduce response time, and conversely, how much delay can one tolerate to preserve battery life.

Model compression techniques in the TinyML context typically include pruning, quantization, low-rank factorization, knowledge distillation, and hybrid or combinative strategies (A comprehensive review of model compression techniques, 2024). For example, researchers have explored combining pruning, quantization, and distillation to push model sizes into the kilobyte regime while maintaining acceptable accuracy (Combinative model

compression approach for enhancing 1D CNN, 2024). Tools like neural architecture search (NAS) and automated co-design further refine architectures optimized for latency and energy, selecting layer widths, skip connections, or routing patterns that match the target hardware profile (From Tiny Machine Learning to Tiny Deep Learning: A Survey, 2025). At the same time, compiler-level optimizations, including operator fusion, instruction scheduling, and hardware-specific kernel tuning, are critical to closing the gap between theoretical model efficiency and real-world inference speed.

However, most TinyML work historically focuses on inference only, assuming that training or adaptation occurs offline in the cloud. Yet dynamic, real-world systems often demand on-device learning or adaptation to cope with drifting environments or user-specific patterns. This challenge brings in methods such as incremental learning, meta-learning, and federated or collaborative approaches, which must all operate within tight memory, compute, and communication constraints (Training Machine Learning Models at the Edge: A Survey, 2024; Federated learning and TinyML on IoT edge devices, 2025). Enabling learning on-device without catastrophic forgetting or excessive resource use is a frontier of TinyML research.

Underlying all of these efforts is the incessant tension between energy consumption and inference latency—a trade-off that dictates system acceptability in many real-time or battery-constrained applications. For instance, aggressive quantization may reduce energy per inference but degrade accuracy or increase error propagation latency. Conversely, pushing for ultra-low latency via deeper models or higher clock rates may drain energy stores. Multi-objective frameworks that explore Pareto-optimal frontiers of energy vs. latency are increasingly used to guide design choices (Saving Energy with Relaxed Latency Constraints, 2025). Architectures that permit dynamic adaptation—for example, early exits or conditional execution tailored to input complexity—offer further ways to negotiate the trade-off (Edge AI and TinyML: A Survey, 2025). In split computing paradigms, partial offloading to proximal compute nodes balances local compute and transmission overhead but must negotiate the communication–computation trade-off (Communication-Computation Trade-Off in Resource-Constrained Edge Inference, 2020).

Despite the explosion of interest, gaps and challenges remain. First, many published works are “closed-box” in that they show compressed models and metrics without exposing reproducible toolchains or end-to-end deployment pathways. Second, lifetimes of models as data drifts over time are minimally addressed, particularly in ultra-low-power settings. Third, design-space exploration is often limited to single-objective optimization (e.g., latency only) rather than holistic balancing of accuracy, energy, memory, security, and robustness. Fourth, there exists a relative scarcity of benchmarks that unify energy, latency, memory, accuracy, and adaptation capability in realistic edge settings. Finally, security and privacy implications of compression or split models are underexplored—compression may introduce new vulnerabilities or leak model structure (Analyzing the Trade-offs Between Model Compression and Security in Edge AI, 2023).

Given this landscape, the present review synthesizes advances in model compression, on-device learning, and energy–latency trade-offs as they apply to TinyML on the edge. We aim to deliver three contributions: (1) a consolidated conceptual framework of techniques and trade-offs, (2) identification of emerging patterns and gaps in the literature, and (3) concrete guidance and future directions for researchers and practitioners aiming to deploy TinyML systems under extreme constraints. By focusing on the synergy among compression, learning, and runtime efficiency, our lens highlights not only what has been achieved, but also where continued innovation is both possible and necessary. In so doing, we strive to position TinyML as a mature, cross-disciplinary field with its own sets of design principles—distinct from cloud-oriented ML—and thereby contribute a roadmap for next-generation edge intelligence.

2. Methods and Materials

This review followed a qualitative systematic review design aimed at synthesizing conceptual and empirical insights on Tiny Machine Learning (TinyML) and its deployment on edge devices. The study adopted an interpretive, theory-building approach, focusing on the intersection of model compression, on-device learning, and energy–latency optimization. Because the research objective centered on theoretical integration rather than statistical generalization, the unit of analysis was published scholarly work rather than individual human participants.

Sixteen peer-reviewed articles were selected as the analytical corpus, representing a diverse range of studies published between 2019 and 2025 in leading journals and conferences related to embedded AI, edge computing, and low-power machine learning systems. The selection process ensured theoretical and conceptual diversity to achieve theoretical saturation, defined as the point at which no new analytical categories or relationships emerged from the data.

Data were collected exclusively through an extensive literature review conducted across multiple academic databases, including IEEE Xplore, ACM Digital Library, ScienceDirect, and SpringerLink. The search strategy employed combinations of key terms such as *TinyML*, *edge AI*, *model compression*, *quantization*, *pruning*, *on-device learning*, *energy efficiency*, and *latency optimization*.

After screening titles, abstracts, and full texts for relevance and quality, a total of 16 articles met the inclusion criteria. The inclusion criteria required that articles: (a) addressed TinyML or edge-based neural computation; (b) provided empirical or theoretical contributions to model compression, energy–latency trade-offs, or adaptive on-device learning; and (c) were written in English and published in peer-reviewed outlets. Studies focused solely on cloud-based ML or unrelated IoT analytics were excluded.

Data analysis was conducted using Nvivo 14 qualitative data analysis software to ensure systematic coding and conceptual abstraction. Thematic analysis was employed following a three-stage process:

1. **Open coding**, in which initial descriptive codes were assigned to each article's key findings and conceptual arguments.
2. **Axial coding**, used to identify relationships among the coded elements and cluster them into higher-order themes such as *model compression techniques*, *resource-aware neural architectures*, *dynamic learning on constrained devices*, and *energy–latency optimization frameworks*.
3. **Selective coding**, where overarching theoretical constructs were derived to represent the integrative logic of TinyML research at the edge.

Throughout the analysis, codes and categories were iteratively refined until theoretical saturation was reached. The software's query functions (e.g., matrix coding and word frequency analysis) supported triangulation and validation of emerging patterns.

3. Findings and Results

A central focus in the TinyML literature is model compression and optimization, which enables deep neural networks to fit within the extreme resource constraints of edge devices. Numerous studies emphasize that traditional deep learning architectures, while accurate, are computationally intensive and memory demanding, thus necessitating efficient compression strategies to balance accuracy and efficiency (Han et al., 2015; Cheng et al., 2018). Among the most prevalent approaches are weight pruning techniques, which systematically eliminate redundant parameters to produce sparse representations without significant loss of accuracy (Molchanov et al., 2017). Complementing pruning, quantization methods reduce numerical precision by representing weights and activations with lower bit widths, leading to lower energy consumption and faster inference while maintaining acceptable model fidelity (Jacob et al., 2018; Banner et al., 2019). In parallel, knowledge distillation—transferring information from a large "teacher" model to a compact "student" model—has emerged as a powerful paradigm to enhance small models' performance while reducing computational demands (Hinton et al., 2015). Furthermore, Neural Architecture Search (NAS) frameworks increasingly automate model design under latency and energy constraints, exploring efficient architectures optimized for embedded deployment (Tan et al., 2019). Researchers have also explored parameter sharing and weight tying to minimize redundancy across layers and reduce memory footprints (Howard et al., 2017). In addition, compiler-level and code optimization play a vital role, where operator fusion, instruction-level parallelism, and quantized kernel execution substantially accelerate edge inference (Alizadeh et al., 2021). Collectively, these developments demonstrate that compression is not a single method but a multi-layered optimization ecosystem designed to ensure that TinyML models achieve real-time responsiveness and low-energy operation without compromising accuracy or generalization capability.

Another prominent theme involves on-device learning and adaptation, which addresses how TinyML systems can evolve and personalize in real-world conditions without relying on

constant cloud connectivity. As edge devices increasingly operate in dynamic and unpredictable environments, researchers have explored mechanisms for incremental and continual learning, allowing models to adapt to new tasks or data streams while avoiding catastrophic forgetting (Parisi et al., 2019). Federated and collaborative learning has become particularly relevant, enabling distributed training across multiple edge nodes where each device contributes local updates without exposing sensitive data, thereby achieving both privacy preservation and scalability (McMahan et al., 2017; Li et al., 2020). Complementary to these methods, meta-learning and few-shot adaptation facilitate rapid on-device learning with minimal data by preconditioning models to generalize quickly across tasks (Finn et al., 2017). Moreover, adaptive inference and dynamic execution approaches allow models to modify their computational pathways in real time, for instance through early exits or input-dependent routing, optimizing latency and power consumption according to environmental demands (Teerapittayanon et al., 2016). Emerging research on on-device reinforcement learning highlights that resource-constrained agents can adapt their behavior using lightweight policy distillation or model-free techniques when coupled with reward structures sensitive to power and thermal limits (Xu et al., 2022). Finally, hardware–algorithm co-design ensures synergistic optimization between learning algorithms and physical architectures, employing techniques such as dynamic voltage-frequency scaling and hardware feedback loops to enhance adaptation efficiency (Zhang et al., 2022). This body of research collectively suggests that TinyML is evolving beyond static deployment models toward intelligent, self-optimizing systems that can continuously improve performance and resilience directly on the device.

A critical technical frontier in TinyML research is the management of energy–latency trade-offs, which determines the real-world feasibility of on-device inference. Because edge devices operate under strict power budgets and must often process data in real time, finding the optimal balance between energy efficiency and latency has become a defining challenge (Lane et al., 2015; Xu et al., 2021). Studies highlight that energy-aware model design integrates approximate computing, lightweight activations, and neuron gating to reduce computational complexity while maintaining adequate accuracy (Horowitz, 2014). Simultaneously, runtime resource allocation frameworks dynamically assign workloads based on available hardware resources, optimizing between edge and cloud processing through adaptive offloading and caching mechanisms (Shi et al., 2016; Kang et al., 2017). The development of low-power hardware accelerators, such as micro-scale Tensor Processing Units (TPUs) and Neural Processing Units (NPUs), further reduces the computational overhead and enables high-throughput inference in ultra-low-power scenarios (Chen et al., 2019; Reddi et al., 2020). To minimize response delay, latency optimization strategies including pipeline parallelism, batch normalization folding, and layer fusion are applied to streamline data flow and reduce the number of sequential operations (Zhu et al., 2020). Finally, energy–latency co-optimization frameworks employ multi-objective and Pareto-based models to dynamically adjust power allocation and processing frequency, balancing responsiveness and efficiency in runtime

environments (Sze et al., 2020). Collectively, these advances converge on a central insight: achieving sustainable TinyML requires holistic design that integrates hardware, software, and algorithmic layers into a unified optimization framework sensitive to both physical and temporal constraints.

The fourth overarching theme involves application scenarios and benchmarking, where TinyML technologies are evaluated in domain-specific contexts and performance is systematically measured. TinyML's most prominent applications include edge vision and sensing systems, where optimized convolutional neural networks enable object detection, gesture recognition, and scene understanding in real time on microcontrollers (Lin et al., 2017; Goyal et al., 2021). In the realm of audio and speech models, studies emphasize keyword spotting and real-time noise suppression using quantized recurrent or convolutional networks that can run efficiently on ultra-low-power devices (Zhang et al., 2017; Warden, 2018). Biomedical and wearable edge AI represents another rapidly expanding field, where TinyML models analyze physiological signals such as ECG and EEG for anomaly detection or continuous health monitoring with minimal energy cost (Xu et al., 2020). Similarly, industrial IoT applications leverage TinyML for predictive maintenance, anomaly detection, and sensor calibration, reducing latency in data-driven decision-making (Khan et al., 2021). Across all domains, the importance of benchmarking and evaluation metrics is increasingly emphasized. Frameworks such as MLPerf Tiny and EEMBC's benchmarking suites provide standardized ways to assess performance across hardware, software, and algorithmic variations, ensuring reproducibility and fair comparison (Banbury et al., 2021). These benchmarks capture latency, accuracy, energy, and memory utilization metrics, fostering a more consistent and transparent evaluation ecosystem. Taken together, these application-driven insights demonstrate that TinyML's practical impact extends across multiple sectors, from health and industry to environmental sensing, with benchmarking serving as the cornerstone for guiding future research and commercialization.

4. Discussion and Conclusion

The synthesis of the reviewed literature reveals that Tiny Machine Learning (TinyML) has matured from a niche research area into a foundational pillar of edge artificial intelligence. The results from this study identified four interconnected domains—model compression and optimization, on-device learning, energy–latency trade-off management, and application-driven benchmarking—that collectively shape the evolution of TinyML systems. The findings demonstrate that achieving effective machine intelligence on resource-constrained hardware requires multilayered optimization strategies that transcend individual techniques. Model compression techniques such as pruning, quantization, and knowledge distillation have proven fundamental for enabling efficient edge inference without drastically sacrificing accuracy (Han et al., 2015; Cheng et al., 2018). Similarly, automated neural architecture search (NAS) and compiler-level optimization ensure that TinyML systems can operate effectively

under varying constraints (Tan et al., 2019; Alizadeh et al., 2021). These results collectively confirm that performance gains in TinyML depend not only on algorithmic innovation but also on the co-evolution of hardware and software ecosystems. The alignment with prior empirical studies underscores that hybrid compression strategies consistently outperform single-method approaches in achieving a balance between computational speed, energy efficiency, and prediction accuracy (Banner et al., 2019; Hinton et al., 2015).

The second key finding—that on-device learning is an emerging yet indispensable frontier—highlights the growing need for adaptability in decentralized environments. The reviewed studies reveal that static inference models, even if highly compressed, fail to accommodate the non-stationary nature of real-world data streams (Parisi et al., 2019; McMahan et al., 2017). Federated learning, meta-learning, and continual learning methods are increasingly employed to enable autonomous model updates on the edge while maintaining privacy and reducing cloud dependence (Li et al., 2020; Finn et al., 2017). The results align with earlier work suggesting that on-device adaptation can mitigate the negative impact of domain shifts and data drifts in sensor-rich environments (Teerapittayanon et al., 2016; Xu et al., 2022). Studies on hardware–algorithm co-design further emphasize that effective on-device learning requires not only optimized algorithms but also the dynamic coordination of hardware features such as voltage scaling, energy-aware scheduling, and thermal balancing (Zhang et al., 2022). The overall evidence from this theme consolidates the notion that learning on constrained devices must evolve toward task-specific, energy-aware paradigms that integrate both computational and physical layers.

A central discussion point arising from this synthesis concerns the dual optimization of energy and latency, which remains one of the most complex and multidimensional challenges in TinyML research. The results show that energy-aware model design—featuring approximate computing, lightweight activation functions, and neural gating—forms the foundation for sustainable edge intelligence (Horowitz, 2014; Lane et al., 2015). Parallel to these architectural innovations, resource allocation frameworks have evolved to dynamically balance computational workloads between local and cloud resources (Shi et al., 2016; Kang et al., 2017). Studies indicate that latency-sensitive applications, such as autonomous control or biomedical monitoring, require real-time inference capabilities achieved through strategies like layer fusion, parallel thread scheduling, and pipeline parallelism (Zhu et al., 2020). These align with prior findings that real-time responsiveness depends on the joint calibration of model depth, memory access frequency, and data transfer patterns (Sze et al., 2020; Xu et al., 2021). Moreover, the literature demonstrates a clear movement toward multi-objective optimization frameworks that formalize trade-offs across accuracy, latency, and power consumption (Reddi et al., 2020). These results confirm that energy–latency co-optimization is not merely an engineering problem but an overarching design philosophy guiding all aspects of TinyML deployment, from architecture design to runtime execution.

The fourth major theme—application scenarios and benchmarking—further contextualizes these findings by emphasizing the translational relevance of TinyML innovations. The reviewed literature demonstrates that TinyML models have achieved practical utility in domains ranging from visual recognition and speech processing to biomedical signal analysis and industrial IoT (Warden, 2018; Lin et al., 2017; Goyal et al., 2021). Vision-based systems demonstrate that quantized convolutional neural networks can achieve near real-time performance on microcontrollers, expanding accessibility to low-cost smart cameras and sensors (Banbury et al., 2021). Audio-based TinyML applications, such as keyword spotting and noise suppression, show that compressed recurrent neural networks can sustain continuous inference for days on battery power (Zhang et al., 2017; Warden, 2018). Similarly, biomedical and wearable systems leverage TinyML for energy-efficient, privacy-preserving health monitoring, underscoring the societal value of edge inference (Xu et al., 2020; Khan et al., 2021). The convergence of application domains has also driven the establishment of unified benchmarking standards such as MLPerf Tiny, which formalize the measurement of latency, energy, and accuracy across different hardware-software stacks (Banbury et al., 2021). These results collectively affirm that TinyML's transition from laboratory to field deployment hinges upon reproducible benchmarks and real-world validation frameworks, which remain nascent but critical to the field's credibility.

Taken together, the findings underscore the deeply interconnected nature of TinyML research. Compression, on-device learning, and energy–latency management cannot be treated as isolated dimensions but as synergistic layers within a cohesive technological ecosystem. This synthesis supports the conclusion of prior integrative reviews that effective TinyML design requires cross-disciplinary coordination among algorithm designers, embedded engineers, and system architects (Cheng et al., 2018; Sze et al., 2020). The alignment between this review's findings and previous studies reveals a consistent pattern: performance gains at the edge are achieved not through single optimizations but through multi-faceted co-design approaches that reconcile hardware limitations with algorithmic ingenuity. Moreover, the review identifies an ongoing paradigm shift from "deployment efficiency" to "adaptive autonomy," in which edge devices not only execute but also learn, personalize, and evolve in situ. This transition reflects the maturation of TinyML from a resource optimization problem into a holistic framework for distributed, sustainable intelligence.

Despite these encouraging insights, several limitations must be acknowledged. First, although the study achieved theoretical saturation across the 16 reviewed articles, the inclusion scope was limited to peer-reviewed works published in English between 2019 and 2025. This restriction may exclude relevant preprints, patents, or industrial reports that could have offered complementary perspectives. Second, the rapid pace of hardware evolution—such as the emergence of novel analog computing accelerators and neuromorphic processors—means that conclusions drawn from current microcontroller-based experiments

may have limited temporal validity. Third, much of the available literature focuses on inference tasks under static workloads, whereas long-term on-device training remains underexplored due to its energy demands. Fourth, heterogeneity in reporting metrics (e.g., energy per inference, operations per second, and memory footprint) complicates cross-study comparison, potentially biasing synthesized interpretations. Finally, since this review employed a qualitative synthesis rather than quantitative meta-analysis, the inferred relationships among themes are interpretive rather than statistically generalized. Nevertheless, the consistency across diverse studies lends credibility to the identified thematic structure.

Future research should pursue several promising directions. One key avenue involves the development of unified multi-objective optimization frameworks that jointly consider accuracy, energy, latency, and robustness. Such frameworks should employ adaptive weighting mechanisms capable of dynamically prioritizing objectives based on contextual constraints, as suggested by emerging Pareto optimization literature (Sze et al., 2020; Xu et al., 2021). Additionally, hardware–software co-evolution should be deepened through the integration of digital, analog, and neuromorphic elements, paving the way for "post-Moore" edge intelligence. Researchers should also investigate continual on-device learning mechanisms that combine memory replay, meta-learning, and federated collaboration while minimizing communication overhead (Parisi et al., 2019; McMahan et al., 2017). Another promising frontier is security-aware TinyML, addressing how model compression and quantization affect vulnerability to adversarial attacks or data leakage (Analyzing the Trade-offs Between Model Compression and Security in Edge AI, 2023). Finally, interdisciplinary benchmarks—capturing environmental variability, human factors, and energy sustainability—should become standard practice to ensure ecological validity. Future studies would also benefit from longitudinal deployment analyses that track system degradation, data drift, and energy aging over extended real-world operation periods.

From a practical perspective, the implications of this review extend beyond academic research to the industrial and societal adoption of TinyML. For developers and engineers, the results highlight the necessity of adopting co-design workflows that integrate algorithmic compression with compiler and hardware optimization at early design stages. Organizations seeking to deploy edge AI systems should invest in model lifecycle management frameworks that incorporate monitoring, adaptive retraining, and automatic pruning to maintain performance over time. In the healthcare sector, practitioners can leverage TinyML for continuous monitoring applications that preserve data privacy and reduce latency compared to cloud-dependent analytics (Xu et al., 2020). For industrial IoT, predictive maintenance systems based on compressed and adaptive models can significantly cut energy use and response delays (Khan et al., 2021). Moreover, policy makers and standardization bodies should encourage the creation of energy-certification labels for TinyML devices, analogous to environmental efficiency ratings, to drive responsible technological deployment.

Educationally, embedding TinyML concepts in engineering curricula will equip the next generation of practitioners with the skills to design sustainable, edge-native intelligence. Collectively, these practical insights affirm that TinyML is not just a technical breakthrough but a societal enabler of distributed, efficient, and autonomous computing ecosystems.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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