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# Addressing limitations of TinyML approaches for AI-enabled Ambient Intelligence

## Position Paper

Antoine Bonneau<sup>1,2</sup>, Frédéric Le Mouél<sup>1</sup>, and Fabien Mieyeville<sup>2</sup>

<sup>1</sup> Univ Lyon, INSA Lyon, Inria, CITI, EA3720, 69621 Villeurbanne, France

{antoine.bonneau, frederic.le-mouel}@insa-lyon.fr

<sup>2</sup> Univ Lyon, Université Claude Bernard Lyon 1, INSA Lyon, Ecole Centrale de Lyon,  
CNRS, Ampère, UMR5005, 69622 Villeurbanne, France

fabien.mieyeville@univ-lyon1.fr

**Abstract.** The integration of Artificial Intelligence (AI) and Ambient Intelligence (AmI) has emerged as a promising approach to creating responsive and contextually aware environments. AmI creates contextually aware environments by seamlessly integrating intelligent technologies, while AI develops algorithms for autonomous learning and decision-making. However, embedding AI within AmI environments faces challenges due to limited resources and energy constraints. While recent research on embedded AI has primarily focused on specific tasks of AmI, our goal is to develop a comprehensive framework encompassing all the necessary components for practical use cases. Through this endeavor, we aim to explore power-aware designs and distributed learning as fundamental approaches to address limited computational resources, energy constraints, and dynamic context variations challenges.

**Keywords:** On-Device Learning · Intermittent Learning · Federated Learning · TinyML · Power Consumption

## 1 Introduction

In the past decade, the fields of Artificial Intelligence (AI) and Ambient Intelligence (AmI) have experienced rapid advancements as two complementary domains. AmI [10] is a paradigm that enables responsive and contextually aware environments by seamlessly integrating intelligent technologies into everyday surroundings. It involves the creation of intuitive systems capable of perceiving, reasoning, and adapting to human presence, needs, and preferences, thereby enhancing user experiences and simplifying interactions with the digital world. AmI has found a natural ally in AI, the domain of computer science concerned with developing intelligent systems capable of performing tasks that typically require human intelligence. It encompasses the development of algorithms and models that enable machines to learn, reason, and make decisions autonomously, mimicking cognitive processes. The intertwining of AI and AmI has been a natural progression [7], as their combined potential holds the promise of unlocking new frontiers in intelligent systems.

How can AmI and AI combination be beneficial? Local data processing and analysis at the deep edge with AI reduces reliance on continuous connectivity and centralized infrastructure, enhancing resilience against network disruptions and limiting personal data exposure. Deploying ML on resource-constrained sensor bring intelligence into AmI hardware. Even though entirely autonomous systems are still out of reach, working on infrastructural bricks is essential in developing AmI's ubiquitous network and can benefit Wireless Sensors Networks Monitoring (WSN) applications. Installing sensors within agricultural fields [18] can facilitate optimized irrigation, fertilization, and pest control. Similarly, in marine ecosystems [35], WSN could help monitor water quality or detect harmful algal blooms [15]. Critical civilian infrastructure elements are prone to damage resulting from environmental factors and operational conditions. The domain of Structural Health Monitoring (SHM) [12] could improve the detection of anomalies or strains by enabling WSN to locally analyze this data, promptly identifying potential issues, and triggering timely maintenance or repairs. In pursuing knowledge and exploring remote and extreme environments like deep space [29], humanity requires safe camps; hence, these isolated habitats can yield substantial benefits to AmI to monitor environmental conditions and resource usage and ensure the safety of explorers.

The integration of AI and AmI presents several challenges. AmI, being inherently integrated into the environment, necessitates miniaturized hardware, thereby imposing constraints on computational resources and autonomy because of the reduced possible size of the battery. Embedded devices, including micro-controller units (MCUs) and sensors, have limited processing power and memory. In the meantime, AI algorithms, particularly Machine Learning (ML) ones, tend to be computationally demanding. Energy consumption is critical for energy-harvesting (EH) and battery-powered devices. The typical efficiencies of energy harvesting techniques suitable for AmI devices range from  $10^{-5}$  to  $10^{-2}$  W [34], while the power consumption of these devices during operational tasks necessary for performing computations, is on the order of  $10^{-1}$  W. Nevertheless, the nodes can operate despite an unfavorable ratio, as they spend a significant portion of their lifespan in standby mode. Few studies look at power consumption, and even fewer take physical measurements, preferring estimates based on datasheets [31], and the few that do only measure microcontroller [23] power consumption neglecting the rest of the hardware. ML models, especially Deep Learning (DL) models, can be large and complex, requiring significant memory and storage resources severely limited in embedded devices. AmI environments are dynamic and subject to context variations. Thus, AI models deployed on embedded devices should be adaptable to such variations and robust enough to handle uncertainties and noisy sensor data.

To address resource limitations in embedding AI within AmI environments, we propose combining Federated Learning and Intermittent Learning with TinyML. Federated Learning enables collaborative model training and resource sharing across multiple devices. Discontinuously powered devices require Intermittent Learning to be usable. When integrated with TinyML, these approaches enable lightweight and efficient deployment of machine learning models on embedded devices, ensuring privacy and adaptability in AmI settings.

## 2 Background and Motivations

### 2.1 Current implementation of Ambient intelligence

The integration of sensors and AI has transformed computing. Initially, sensors relied on rule-based frameworks but have now advanced to ML-based approaches. They have transitioned from plugged-into power sources to mobile with energy harvesting or charging stations. For instance, researchers develop wearable health monitoring devices powered through energy harvesting for continuous operation, while autonomous vacuum cleaners recharge at dedicated stations.

*Semantic AI* is a branch of AI that focuses on understanding and interpreting the meaning of data and information. It involves using rules and algorithms to process and analyze data to make intelligent decisions and take appropriate actions. AmI implementations traditionally leveraged this AI to emulate contextual intelligence [22]. For instance, intelligent agents equipped with semantic knowledge can autonomously control home appliances. In healthcare, Semantic AI is being utilized to assist individuals in their daily activities, such as reminding them to take medication.

*ML-based AI* [10] has improved the performance and complexity of tasks previously performed with semantic AI and introduced new possibilities such as language, gesture, emotion, and human activity recognition. Current models are mostly trained using supervised or reinforcement techniques. Nevertheless, rule-based systems or supervised learning lack the necessary robustness to effectively adapt to a continuously evolving real-world environment that deviates from its initial design and deployment conditions.

### 2.2 Energy consumption concerns in TinyML

The essence of intelligent sensors lies in their ability to learn, which is now facilitated by TinyML techniques [11,25]. On-device learning empowers the local processing of information, primarily focusing on inference tasks, following the refinement of a pre-trained model [37]. On the other hand, autonomous systems and EH technologies enable self-powered AmI applications but imply a tight energy budget and have to cope with inevitable power shortages. The energy storage supporting EH [27] is a challenge in itself: batteries have higher energy density and provide constant (but relatively high) voltage, while supercapacitors have low energy density and provide unstable (but relatively low) voltage. On the other hand, supercapacitors are exposed to significant depletion, while batteries have only a few charge/discharge cycles. Due to the compact size of the sensors, the batteries employed must be small, typically ranging from 600 to 700 mAh [4]. Consequently, these batteries can only sustain an always-on device's requirements on a daily timescale or monthly, considering periods of sleep.

Previous works have shown that it is possible to use advanced AI solutions despite the memory constraints of low-end devices [20,25]. Lin et al. [17] has successfully fine-tuned a human recognition model on an STM32F746, a 32 bits microcontroller typical of low-end devices using less than 256 KB of RAM and 1 MB of Flash. Sudharsan et al. [31,32] employed smaller models and trained them from scratch using

a reformable offline approach [24] on low-end MCUs. However, their approach solely relied on the datasheet information to estimate the computational requirements for training and inference processes. Profentzas et al. [23] optimized a pre-trained activity-recognition neural network on an nRF-52840 SoC featuring: a 32-bit ARM Cortex-M4 with FPU at 64 MHz, 256 KB of RAM and 1 MB of Flash physically measuring energy consumption. However, they limited their instrumentation to the MCU and did not reflect the actual energy-guzzling components consumption of a board such as the voltage regulator.

### 3 Concrete Use Cases

When establishing a cloud link for WSN proves to be arduous, cloud processing of ML models may be impossible. In certain circumstances, monitoring applications assume criticality while simultaneously encountering challenges in terms of connectivity. The accessibility of these environments to human presence may present challenges or render them permanently inaccessible once the devices are activated.

*Environmental Monitoring* Utilizing ML on sensors within agricultural fields [18] can facilitate optimized irrigation, fertilization, and pest control. Similarly, in marine ecosystems [35], ambient intelligence implemented in a WSN would help monitor water quality, tidal behavior changes, detect harmful algal blooms, and contribute to conservation efforts. Civil Engineering critical infrastructure elements such as bridges and dams are prone to potential damage from various environmental factors, operational conditions, and daily interactions with multiple agents. This is the domain of Structural Health Monitoring (SHM) [12].

*Habitats Optimized for Missions of Exploration* In the pursuit of knowledge and exploration of remote and extreme environments like deep space [29], or ocean depths, humanity requires safe camp infrastructure to accomplish missions. By deploying sensor networks, these habitats can be monitored for environmental conditions, resource usage, and the safety of explorers. Embedded intelligence enables local analysis on the sensor nodes, facilitating anomaly identification and timely alerts. This proactive approach ensures the success of exploration missions and the well-being of personnel in challenging environments.

### 4 Challenges and Elements of a conceptual framework

In the realm of embedded systems, limited memory and power outages pose significant challenges. We want to develop a cross-platform framework departing from a lightweight RTOS addressing presented issues. We want to compare low-level programming ease, relevant frameworks [21,14], and microcontroller operating systems [1] to analyze associated overhead. To facilitate comprehensive evaluations, we propose assessing energy consumption in MCU boards within the context of AmI by focusing on individual tasks that can be examined independently. We will evaluate data acquisition and cleaning processes (section 4.1), analyze trade-offs of ML models

for classification and regression in a power-aware context (section 4.2), and assess the energy consumption of various communication protocols and distributed learning (section 4.3).

#### 4.1 Minimizing hardware requirements through Data Reduction

Employing data reduction techniques can decrease the volume of manipulated data by selectively extracting helpful information from input signals, thereby mitigating memory constraints. A consequential advantage of data reduction is the reduction in processing time needed for analysis or computation.

*Adaptive Sampling* [33,28] entails the dynamic selection of representative data points from large datasets, which efficiently utilizes computational resources. The computational burden is significantly reduced by intelligently sampling only the most informative data instances. Moreover, adaptive sampling reduces the overall time required for model training and inference, enabling time-sensitive applications to operate effectively within the limitations of embedded systems.

*TimeSeries Segmentation* [6,19,13] involves partitioning time-varying data into smaller, more manageable segments based on characteristic patterns and behaviors. This technique enables the selective analysis of specific segments rather than processing the entire time series data. The segmentation or *change point detection* methods are similar to feature extraction and would help focus on relevant portions without requiring a demanding Convolutional Neural Network (CNN).

#### 4.2 Meeting short and long-term time constraints

One significant resulting challenge of EH systems is the occurrence of power shortages that may hinder continuous operation. By carefully considering power availability and adapting system behavior accordingly, embedded computing can effectively operate within energy-limited environments. Limited device accessibility and updates make it imperative to imbue devices with self-assessment capabilities during the design stage. This challenge entails enabling devices to evaluate and analyze their understanding of the environment. By incorporating self-assessment and adaptation mechanisms, devices can autonomously maintain and update their understanding of the environment, ensuring effective operation even in dynamic or disrupting circumstances.

*Intermittent Learning* refers to a learning paradigm that manages irregular or sporadic availability of training data or computational resources. Lee et al. [16] introduced Intermittent Learning as a way for EH computing platforms to perform machine learning tasks effectively and efficiently. Among the frameworks for intermittent learning that later emerged, [2] developed *REHASH*, a tool helping design adaptive IoT workflow heuristics. They evaluated their work by running activity recognition and greenhouse monitoring applications using an MSP430FR5994 Launchpad.

*Incremental/Continual Learning* refers to a machine learning paradigm that focuses on the ability of a model to learn from new data incrementally over time without requiring retraining from scratch [30]. Ren et al. [26] have tested their incremental online learning algorithm TinyOL on an Arduino 33 BLE board in a default detection application for USB fan vibrations data. Continual learning involves updating and expanding the model’s knowledge while preserving previously learned information, enabling adaptation to new tasks or concepts without significant performance degradation. Until recent advances, retraining a model that has experienced concept drift in its evaluated data entails transmitting the data through the internet to a server responsible for generating a new model [24] subsequently redistributed to the hardware executing inferences.

### 4.3 Enabling devices collaboration using Federated Learning

Federated Learning (FL) addresses the challenge of distributed data storage by allowing entities to collaboratively train models without sharing their data. FL is classified into two categories: Centralized Federated Learning (CFL) and Decentralized/Distributed/Serverless Federated Learning (DFL) [3,36]. CFL uses a central server, while DFL enables decentralized aggregation of model parameters. DFL finds significant utility in overcoming AmI device constraints disconnected from the internet and centralized servers. In such scenarios, DFL serves as a means to overcome these individual deficiencies by leveraging the collective power of the network. DFL allows for collaboratively training models and achieving higher intelligence without relying on solid individual capabilities. This collective approach could virtually circumvent computational weaknesses and memory constraints, providing a robust solution for AmI systems if in-situ and collaborative processing are balanced enough to justify communication overhead.

Some works have already started addressing the constraints imposed on intelligent sensors and the distribution of AI calculations in embedded systems. Dai et al. [9], with *DispFL*, have proposed to act on communication costs using personalized FL and decentralized learning. Costa et al. [8] designed a framework to enable the deployment of decentralized learning in resource-constrained devices. They evaluated their contribution on a STM32L4R5ZIT6 MCU over some Artificial Neural Network models.

In the context of AmI, the implementation of FL necessitates addressing the inherent challenges posed by the fluctuating size of the learning network and the varying availability of energy resources among participants. Learning occurs exclusively among active nodes, which may vary across iterations. Hence, adopting specific strategies to ensure the FL process’s reliability and expeditious convergence is imperative.

## 5 Conclusion and Future Work

We claim that the challenges linked to incorporating AI into Ambient Intelligence (AmI) settings can be successfully resolved by integrating Federated Learning, Intermittent Learning, and TinyML [5]. Combining those approaches and data reduction

techniques enables collaborative model training and resource sharing across devices while addressing the sporadic availability of training data and computational power. Overall, this approach holds great potential to enhance the performance and resilience of embedded systems in resource-constrained environments, enabling the advancement of intelligent systems in AmI and unlocking new possibilities. We will evaluate solutions on a testbed composed of piezoelectric patches on an aluminum plate. TinyML sensors must collect and analyze data to identify vibration sources and distance and evaluate default type and severity. We then want to focus on distributed learning strategies for SHM tasks with separate processing nodes for piezoelectric signals.



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