Advancements in Machine Learning in Sensor Systems: Insights from Sensys-ML and TinyML Communities

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***Abstract*—The integration of machine learning (ML) algorithms with edge sensor systems has fundamentally transformed numerous industries. This convergence empowers real-time data processing, analysis, and decision-making at the network's periphery. This paper investigates the latest advancements in this domain by examining two key communities: Sensys-ML and TinyML. While Sensys-ML concentrates on optimizing ML for sensor systems, TinyML prioritizes deploying ML models on resource-constrained devices. Through a critical analysis of these communities' contributions and interactions, this work aims to provide a comprehensive overview of cutting-edge methodologies, persistent challenges, and promising future directions for ML at the edge within sensor systems. By tracing the trajectory of advancements in this field, we offer a critical reflection on the broader research landscape and its scope. Additionally, we identify emerging research areas as reflected in prominent forums and underscore persisting knowledge gaps that call for further investigation.**

***Index Terms*—Machine Learning, TinyML, UltraML, Sensor systems**

I. Introduction

Machine learning at the edge, a transformative approach, involves deploying ML models directly on sensor devices, facilitating real-time data processing without relying on cloud-based servers. This paradigm shift has spurred notable advancements across various domains, including healthcare, agriculture, environmental monitoring, and urban planning.

Two prominent communities are among the leading contributors to the progress of ML at the edge: Sensys-ML and TinyML. Sensys-ML specializes in advancing machine-learning techniques tailored specifically for sensor systems. On the other hand, TinyML focuses on deploying ML models on resource-constrained devices with limited computational power and memory.

This article aims to delve into recent progress and future prospects of machine learning at the edge by drawing insights from discussions and developments within these communities.

II. Advancements in Sensys-ML and TinyML

The Sensys-ML community is committed to enhancing machine-learning techniques specifically designed for sensor systems. Recent research endeavours in this domain have centred on developing algorithms capable of effectively processing sensor data, extracting meaningful features, and facilitating predictive analytics at the edge.

Conversely, the TinyML community is dedicated to deploying ML models on resource-constrained devices with limited computational capabilities. This entails developing lightweight algorithms and model optimization techniques to ensure efficient inference on edge devices.

Noteworthy advancements in TinyML include the creation of compact neural network architectures, innovative quantization methods, and sophisticated model compression techniques. Additionally, the community actively engages in the creation of tools, frameworks, and libraries tailored for deploying and managing ML models on microcontrollers and embedded systems.

A. Conferences and workshops

In recent years, the Sensys-ML (Sensor-based Machine Learning) and TinyML communities have emerged as dynamic ecosystems, fostering collaboration between academic and industrial researchers to propel the development of intelligent sensor technologies to new heights. Their collective efforts have sparked significant advancements in this rapidly evolving field, with groundbreaking innovations continually reshaping its landscape.

These communities actively engage with leading sensor research conferences and workshops, where their work is showcased and discussed. These events serve as crucial platforms for researchers and industries alike to present their latest findings, exchange ideas, and receive invaluable feedback from peers. Moreover, they provide fertile ground for forging new collaborations and partnerships, driving further innovation and progress in the field.

This article undertakes a comprehensive analysis of the research and presentations showcased at various renowned conferences and published in esteemed journals. By synthesizing insights from these diverse sources, it seeks to provide a comprehensive overview of the current state and future trajectories of sensor-based machine learning and tiny machine learning technologies.

1) Nature Machine Intelligence [62] is a renowned academic journal that specializes in leading-edge research

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within the field of machine learning, with a particular emphasis on its applications involving sensor data.
2) Nature Electronics [63] is a scholarly publication that specializes in research concerning electronic devices, particularly emphasizing their capabilities for machine learning applications.
3) ACM Sensys [64] is a conference that concentrates on sensor systems and their applications. It covers various aspects such as sensor design, data processing, and networking.
4) The IEEE/ACM EWSN conference [65] focuses on investigating topics related to embedded wireless sensor networks, which are essential for deploying Sensys-ML and TinyML solutions.
5) The IEEE Sensors conference and journal [66] covers a wide range of topics related to sensor technology, including areas pertinent to Sensys-ML and TinyML.
6) The IEEE/ACM Sensys-ML workshop [67] is focused solely on sensor-based machine learning, providing a platform for discussions regarding recent advancements and challenges in the field.
7) MLSys [68] Explores the synergy between systems research and machine learning, with potential applications for Sensys-ML systems.
8) The TinyML Foundation summits, coordinated by the TinyML Foundation [69], gather researchers and industry leaders who are dedicated to advancing TinyML technologies.
9) The MLCommons TinyML Benchmark [70] offers a standardized platform used to assess and compare the performance of TinyML models across different tasks.

B. Emerging applications

Advancements in sensor technology, computing power, and machine learning have spurred a wave of innovative applications in recent years [3]–[6], [12]–[15], [19], [22], [24], [25], [31], [36]. These applications, detailed in Table I, fall into prominent categories like smart wearables and MedTech. Smart wearables have transcended basic functionalities like motion tracking [1], [18], [29], [45] and gesture recognition [11], [16], [17], [28], [30], [34], [44], [46], [50] to facilitate the reconstruction of full avatars [41] and digital twins [2]. Similarly, a tiny, low-power neural network called Tiny Eats GRU is designed for wearable devices to accurately classify eating episodes using minimal resources [57]. The research in wearable opens doors to exciting possibilities in augmented and virtual reality. Other applications include Video recognition and prediction [10], [34], Position and localization estimation [9], [23], [29], [30], [33], [38], [39], Anomaly detection [20], [21], Virtual AI assistant (LLM), Voice user interfaces [51] and smart RF sensing.

C. Emerging Hardware

Sensor Integration and Miniaturization for TinyML/Sensor-ML is driven by MEMS technology, enabling smaller, wearable devices with integrated sensors on a single chip. Bio-

TABLE I
EMERGING APPLICATIONS

Applications	Research paper (Year)	Notes	ML
Human activity recognition	[45](2021)	This study collects data from wearable sensors during daily activities, processes it statistically to extract time-sequential information, and utilizes kernel-based discriminant analysis (KDA) to enhance clustering and discrimination between activity classes.	LSTM + NSL
Human activity recognition	[46](2023)	MESEN framework leverages unlabeled multimodal data to enhance unimodal human activity recognition (HAR).	CNN and Contrastive Learning
3D wrist tracking using smart-watches	[50](2022)	The RTAT leverages a multitask deep learning approach with an attention mechanism and a novel smooth loss function to achieve superior performance.	DNN
Full-Body Motion Tracking	[41](2022)	This study introduces wearable MXene sensor modules with on-device machine learning (inference) for accurate full-body motion capture and avatar reconstruction.	CNN training (offline), inference (online)
Measurement correction	[38](2021)	This study shows a Multi-Layer Perceptron (MLP) can correct errors in angular sensing systems caused by mechanics, and explores a method to analyze the learned features for better understanding and usability of neural networks in measurement tasks.	MLP
Position (localization) measurement	[39](2021)	This paper proposes using deep generative models to address imbalanced data issues in indoor positioning based on Bluetooth fingerprints, achieving better precision than existing methods.	VA and CVA
Signal analysis	[35](2021)	This paper proposes a new method using time-frequency analysis to classify normal and abnormal heart sounds (PCG) with high accuracy, potentially aiding medical diagnosis.	FSST and SVM
Mass Spectrum prediction (Odor perception)	[32](2021)	This study demonstrates successful prediction of mass spectrum features based on desired odor impressions using a deep neural network, paving the way for designing new fragrances.	DNN
Classification of Colorectal Cancer Polyps	[27](2022)	This study explores using machine learning on 3D texture data from a special sensor to improve early detection of colorectal cancer polyps.	Transfer Learning

integrated sensors further advance health monitoring by embedding sensors within the body. Heterogeneous integration merges multiple sensors and processing units on a single chip, facilitating complex data collection in compact devices. Focus on lower power consumption includes ultra-low power processors and energy harvesting for battery-powered TinyML applications. Security [26] and privacy measures are implemented through hardware advancements to safeguard user data throughout collection, processing, and storage. The survey [42] presents how machine learning is implemented on resource-constrained devices, focusing on microcontrollers. The article [43] delves into a novel concept in sensor design: machine learning-inspired sensor design. Traditionally, sensors are constructed before developing data analysis methods to interpret their output. However, this innovative approach poses the question: ”How could we enhance existing sensors if we had access to today's advanced computational tools during their initial design?” The central concept involves integrating computation and machine learning directly into sensor hardware during the design phase, a process known as ”computational sensing.” This approach promises to significantly enhance sensor performance. The article showcases examples from computational imaging, where this methodology has already proven beneficial. It discusses specific technologies such as compositionally engineered nanowires and on-chip spectral encoders, which leverage machine learning to achieve improved performance.

The paper [25] evaluates a new sensor (ISM330AILP) with built-in processing for on-sensor activity classification. They designed neural networks for real-world scenarios and achieved good performance using the sensor's processor. While memory limits full-precision networks, the processing speed is comparable to a standard processor for these tasks. They also showed significant speedups for binary neural networks.

The paper [72] proposes TinyissimoYOLO, a family of tiny deep-learning models for object detection on smart glasses. These models achieve good accuracy with low energy consumption (lasting 9.3 hours on a small battery) and fast inference times (18 fps) on a custom smart glasses prototype with a low-power processor.

III. Advancement in Fundamental research

BlastNet [48] utilizes an innovative block-level Neural Architecture Search (NAS) method to create duo-blocks, considering both computing characteristics and communication overhead. These duo-blocks are optimized during design and dynamically scheduled to maximize resource usage across heterogeneous CPU and GPU at runtime to meet time-critical applications demands.

Techniques such as transfer learning [1], [27], federated learning [19], [40], [49], [56], accelerators [37], attention mechanisms [83] have been explored to enhance the performance and efficiency of ML models in sensor networks. Federated Learning (FL) lets many devices train a shared AI model together without sharing private data. However, traditional FL methods struggle with devices having different processing power. Slower devices (stragglers) drag down training. Additionally, real-world issues like network drops and power outages can further limit scalability. To address these issues, researchers developed asynchronous training approaches. These fall into two categories: (1) Asynchronous FL (AFL) updates the model immediately upon receiving information from any device, reducing wait times but increasing communication costs and potential data staleness.(2) Semi-asynchronous FL (SAFL) combines synchronous updates with flexibility, improving efficiency by avoiding waiting for stragglers. However, current SAFL frameworks have limitations that hinder real-world performance.

FedSEA [49] is proposed as a semi-asynchronous Federated Learning (FL) framework tailored for extremely heterogeneous devices, addressing challenges in accuracy and efficiency. By balancing aggregation frequency and predicting device update arrival times, FedSEA significantly improves accuracy by 44.34% and reduces time and energy costs significantly compared to existing FL methods.

The research paper [51] introduces VocalHR, a system that leverages Voice User Interfaces (VUIs) for heart activity sensing. It exploits the “voice-heart modulation effect,” where the heart's rhythm subtly influences vocal cord vibrations. By analyzing specific voice features from various vocal organs, VocalHR employs deep learning (LSTM) to translate these features into heart activity data. The study investigates the influence of heart activity on the voice production process and introduces corresponding biological lung-larynx and pharynx VocalHR features to characterize heart activities in voices. Furthermore, a novel cardiac activity reconstruction model is proposed, capable of extracting cardiac information from features and reconstructing cardiac activities. The authors suggest employing a discriminator with wavelet decomposition to supervise the configuration of the data-driven demodulator. Extensive experiments demonstrate the effectiveness of VocalHR in detecting cardiac activities from human voices.

Moreover, efforts have been made to address the challenges of data heterogeneity, noise, security [25], and energy constraints [55], [56] inherent in sensor data streams.

ExecuTorch is an end-to-end solution for enabling on-device AI across mobile and edge devices for PyTorch models [71]. It discusses what ExecuTorch is and what its key value propositions are. ExecuTorch is part of the PyTorch Edge ecosystem. Some of the key value propositions of ExecuTorch are portability, productivity, and performance.

The cONNXr [75], the C library allows running machine learning models (exported as .onnx files) on embedded devices with limited resources. It works with various training frameworks and avoids complex C++ or hardware acceleration for broad compatibility.

The review [73] explores challenges like limited memory and proposes co-designing algorithms and systems (like MCUNet [74]) to enable TinyML applications on devices with limited processing power. It also explores future directions for TinyML, including on-device training techniques.

In benchmarking direction, BiomedBench [77], similar to Medperf [79], is a suite of real-time biomedical applications for wearables. It allows hardware designers to evaluate ultra-low power platforms and software developers to choose the best platform for their application, aiming to improve overall bioengineering system design.

A new compact Graph Neural Network (GNN) architecture called LR-MPGNN for radio resource management [80], significantly reduces model size and parameters (up to 98%) using a low-rank approximation technique, achieving similar performance to the original model.

A new on-device learning system for TinyML keyword spotting that adapts to user speech patterns without needing large amounts of data or processing power is presented in the paper [81]; this method improves accuracy on unseen speakers and works well on battery-powered devices.

TinyFormer [82] is a framework for developing efficient transformer models [7], [8] that can run on tiny devices with limited resources. It uses a combination of search techniques (SuperNAS & SparseNAS) and a specialized deployment engine (SparseEngine) to achieve high accuracy (96.1% on CIFAR-10) while fitting within memory and storage constraints of microcontrollers. This opens doors for using powerful transformers in TinyML applications.

FLAML [53], a fast and lightweight library for AutoML that automates learner and hyperparameter selection for ad-hoc datasets using low-cost trials, achieving high accuracy under tight resource constraints.

In summary, there has been a notable rise in innovative solutions addressing the challenges of deploying machine learning models on devices with limited resources [55], [58]–[61], [84].

IV. Challenges and Future Directions

Edge/sensor machine learning has achieved remarkable progress [42], [46], [52], [55], [84], but several key challenges remain to be addressed. These challenges include ensuring model robustness in variable environments, developing scalable models that can adapt to growing data demands, safeguarding data privacy, and minimizing energy consumption on resource-constrained devices. Future research directions lie in exploring novel algorithms for anomaly detection [55], continuous learning [85], diffusion models [86], efficient implementations of large language models (LLMs) [87], neuromorphic architectures [54], adaptive model optimization techniques [77], [78]. Interdisciplinary collaboration between researchers in sensor networks, machine learning, and embedded systems will be critical in overcoming these challenges and unlocking the full potential of edge intelligence.

V. Conclusions

In conclusion, advancements in machine learning at the edge, as witnessed through the contributions of Sensys-ML and TinyML communities, have paved the way for transformative applications across various domains. By developing tailored ML techniques and deploying lightweight models on resource-constrained devices, researchers have enabled real-time analytics and decision-making at the edge of the network. However, several challenges persist, necessitating further research and innovation. Through continued collaboration and interdisciplinary efforts, the future of machine learning at the edge holds immense promise for creating intelligent and autonomous sensor systems.

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