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TinyML and Embedded Artificial Intelligence for Intelligent, Healthcare, Speech Processing, and Assistive Applications: A Comprehensive Review

Sudipta Mondal[1], Dr. Geetika Narang[2], Prof. Vishal Shinde[3], Prof. Sai Takawale[4]

[1]PG Student, Dept. Of Computer Engineering., Kj's Educational Institutes Trinity College of Engineering And Research
[2]HOD, Dept. Of Computer Engineering., Kj's Educational Institutes Trinity College of Engineering And Research
[3,4]Assistant Professor, Dept. Of Computer Engineering., Kj's Educational Institutes Trinity College of Engineering And Research

ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are key technologies for creating intelligent systems in healthcare, speech processing, assistive technology, IoT, and other areas. Tiny Machine Learning (TinyML) enables ML models to run on microcontrollers with extremely limited computing, memory and power resources. In this research, we will look at intelligent edge systems and various challenges associated with them, such as computing constraints, model complexity and real-time requirements, as well as tradeoffs with energy, data security, and privacy. We also look at the challenges with cloud-based AI systems for healthcare and assistive technology. We will perform a literature review on TinyML and other embedded AI systems for constrained and resource-poor environments. We will look at different techniques to reduce the size of AI systems and to train them to run on resource-constrained systems. We will also look at other intelligent systems in speech, language and communication technologies for people with speech and language disabilities. We will look at different intelligent systems for healthcare and rehabilitation. Finally, we look at various technologies for the IoT, including intelligent systems with embedded intelligence for real-time analysis and decision making. We look at various types of intelligent systems and AI technologies, as well as the issues associated with integrating and deploying them in the real world. We look at barriers including reliability, security, privacy, and the tradeoffs with real-world deployment. We also look at various research approaches and evaluation criteria. We will propose plans of actions and research guidelines for developing more secure, explainable, and energy-efficient AI systems.

Keywords: TinyML, Embedded Artificial Intelligence, Machine Learning, Internet of Things (IoT), Edge Computing, Speech Recognition, Healthcare Monitoring, Assistive Technology, Deep Learning, Explainable AI, Energy Efficiency, Cybersecurity.

1. INTRODUCTION

Machine Learning and Artificial Intelligence are revolutionizing the world of computing by allowing computers to learn and perform intelligent tasks such as classification and prediction, and to understand natural languages and recognize objects. New interactive and intelligent applications, often required to run in real time, are becoming increasingly common. This has directed the research toward distributed and decentralized AI architectures, making the processing of AI applications feasible on edge and embedded devices.

Tiny Machine Learning (TinyML) is a relatively new technology which allows executing on low-power microcontrollers and other resource-constrained devices, Artificial Intelligence (AI) models and Machine Learning (ML) models trained to perform intents like classification, recognition, prediction, and to interact with users. Due to these characteristics, TinyML reduces the need for communication, improves response time and allows computing intelligences locally on resource-constrained devices [1], [11].

Research in the field has recently increased, and several potential uses of TinyML have been identified such as in health care, intelligent sensing, speech processing, and wearable computing. In their survey, Capogrosso et al. [1] presented methods and technologies for TinyML, along with case studies and potential applications in AI-powered edge devices. Similarly, Abadade et al. [11], covered the theoretical aspects of TinyML, along with architectures and methods of implementation.

Embedded AI in the field of healthcare allows for the continuous monitoring and smart analysis of physiological signals. Ali et al. [12] looked at a convolutional autoencoder for real time PPG-based blood pressure monitoring using TinyML. Arthi and Krishnaveni [13] looked at the use of TinyML and AI for efficient healthcare decision-making.

An emerging area of TinyML is speech processing. Deep learning has allowed for breakthroughs in fields such as speech recognition and speech enhancement [2], [8]-[10]. There have also been advances in wearable intelligent systems to help people with speech impairments to improve communication [3].

Also, there have been TinyML, embedded AI, and IoT based systems to develop advanced and rehabilitative assistive systems [4]. This convergence allows for practical smart, safe, and secure systems in a small form factor. These projects highlight the immense potential in the integration of several interdisciplinary technologies for practical healthcare applications in an industry setting.

A. Contributions

The contributions of this review paper are as follows:

- To provide a general view of TinyML and embedded Artificial Intelligence.
- To study lightweight Machine Learning architectures and methods for optimizations for resource-constrained devices.
- To review architectures and methods for AI-based speech recognition and enhancement, and semantic speech processing.
- To study TinyML applications for Healthcare monitoring and other wearable intelligent systems.
- To review AI-based robotic rehabilitation and other assistive technologies.
- To review research literature and compare their contributions and application domains.
- To analyze the gaps in research, focusing on areas such as energy consumption, model complexity, security, privacy, and dependability.
- To identify areas for future research to build trust, intelligent, explainable, and secured embedded AI systems.

2. BACKGROUND

TinyML and embedded artificial intelligence merge to allow machine learning algorithms to be executed on low power, edge devices. Traditional AI systems rely on the cloud to process data and create a constant flow of communication between edge devices and the cloud. Embedded AI systems process data and create inferences locally, resulting in near-instantaneous feedback.

1) Tiny Machine Learning (TinyML)

Tiny Machine Learning refers to the execution of machine learning algorithms on low power devices. It allows edge devices to process data and create local inferences even with very limited computational resources.

The main features of TinyML include:

- Very limited memory and computational requirements
- Very low power consumption
- Real time data processing
- Local classification and prediction
- Less dependency on cloud resources
- Local data processing, hence improved data privacy

Capogrosso et al. [1] and Abadade et al. [11] discussed TinyML architectures, resources efficient machine learning deployment and implementation strategies.

A. Embedded Artificial Intelligence

Embedded AI allows devices to become "smart" by processing the data and making inferences and decisions without communicating with external servers.

B. AI-Based Speech Processing

Speech Processing is concerned with utilizing artificial intelligence and deep learning for speech recognition and classification, audio signal improvement and other related tasks for different practical applications.

Input 2 reviews AI-based speech classification and enhancement methods for speech and language disorders. Chang et al. [8] presented SpeechPrompt for speech language model prompts in speech processing. Deep learning approaches for automatic speech recognition are reviewed by Ahlawat et al. [9], and semantic speech analysis using ML and DL is reviewed by Tyagi and Szénási [10].

C. Healthcare Monitoring and Wearable Systems

AI in healthcare systems that integrate machine learning and other AI technologies for monitoring health conditions of patients and aiding healthcare professionals in making decisions are reviewed by Nazari et al. [11].

A convolutional autoencoder for blood pressure monitoring using PPG is reviewed by Ali et al. [12] using TinyML. Arthi and Krishnaveni [13] reviewed TinyML integrated with explainable AI for healthcare decision support. A wearable intelligent throat system for stroke patients with dysarthria is reviewed by Tang et al. [3].

D. Assistive Technologies and Rehabilitation Robotics

Pecht and Johnson argue that the computing and communication needs of current rehabilitation technology can be met through advanced systems integration. The expected expansion of the Internet of Things will provide opportunities to create affordable, non-invasive wearable assistive and rehabilitative technologies. Gherman et al. [4] surveyed robotics systems for hand rehabilitation, tracing the development of these systems from previous technologies, and identifying emerging trends.

E. Security and Privacy in Embedded AI

It is essential that embedded AI systems meet the security and privacy requirements because the data processed by these devices is often personal, physiological, and behavioral.

Butt et al. [15] presented a case study of a secure and private embedded machine learning system for emotion-aware facial recognition. Costa and Pinto [18] analyzed different types of attacks and defenses for a quantized neural network. Dehrouyeh et al. [20] studied cybersecurity in TinyML for electric vehicle charging systems.

3. LITERATURE REVIEW

Capogrosso et al. [1] present a review of TinyML focused on using machine learning on low-power, small, and low-cost edge devices. The review identifies opportunities and challenges for using deep neural networks, makes recommendations on reducing memory and computational requirements, and identifies how to improve the efficiency of models. The review shows how lightweight models are essential when cloud connectivity is unavailable. This research provides the basis for developing a framework to optimize speech classification models for microcontroller-based hand rehabilitation systems.

Remya et al. [2] examine the utilization of artificial intelligence (AI) in classification and enhancement of speech for various speech and language disorders. The review identifies numerous AI methods, their applications, and areas for future research. It illustrates the use of intelligent speech processing to promote speech assessment and other assistive technologies. This research is relevant to the development of speech command recognition systems that are robust to variability in the acoustic environment.

Tang et al. [3] analyze a wearable intelligent-throat system for stroke patients to facilitate natural speech. The study focuses on wearable intelligent signal processing to develop a system for communication when natural speech is not possible. The study illustrates the use of wearable technology for improving accessibility and communication. This research is relevant to develop intelligent systems for rehabilitation of communication and speech.

Gherman et al. [4] review robotic systems for hand rehabilitation, showing their evolution, present uses, and future studies. The paper reviews the roles of robotics in support of hand movement and rehabilitation activities. The paper describes rehabilitation system design and control, and other assistive technology components of rehabilitation systems. It presents a case for controlling a robotic rehabilitation system using the speech of the subject.

Balbi et al. [5] review the use of the MAX78000 microcontroller for embedded AI in the Internet of Things. This includes developing and deploying AI models to edge devices. The paper emphasizes resource and memory limitations in embedded devices. The paper focuses on hardware and algorithms for running machine learning models. This is useful for embedding speech classification models in microcontrollers for controlling rehabilitation systems.

Rascon et al. [6] take a multi-agent approach to auditory scene analysis focusing on localization correction and speech quality improvement through feedback between processing units. This research describes the benefits of feedback and synchronization between processing elements. This is useful when dealing with complex, unpredictable acoustic environments. This describes a system of feedback, noise, and speech robustness that is useful for investigating improvements in speech recognition.

Tantaroudas et al. [7] propose a solution for extending multilingual education in XR based on modular AI services for speech processing, translation, and sign-language rendering. The solution shows how modular AI can enable accessibility and communication across languages and different ways of interacting. The

solution outlines the need for integrated intelligent processing in various domains to build a unified system. The ideas presented provide a context for modular speech processing architectures for assistive technology

Chang et al. [8] present SpeechPrompt, which uses speech language models with prompting techniques for various speech-related tasks. The work examines speech models and their ability to be prompted for various processing requirements. The work focuses on speech-related tasks and the need for flexible, AI-based, speech-related processing. The work investigates shared representations in AI models for various tasks. The approach is different from conventional TinyML classification; however, the work provides a framework for new methodologies in speech processing.

Ahlawat et al. [9] survey deep learning approaches and methods in automatic speech recognition (ASR) systems. The paper discusses recent trends in speech recognition technology using deep neural networks. It covers the role of deep learning in the improvement of ASR systems and available related approaches. The survey aids in the selection and assessment of the appropriate neural architectures for speech-command recognition. While the project focuses on the recognition of command words for a given device control, there are other deployment constraints that also need to be considered.

Tyagi and Szénási [10] give a broad review of machine learning and deep learning techniques for interpreting spoken language. The paper focuses on the methods for analysis and interpretation of spoken language. It concentrates on the contribution of intelligent learning in understanding speech and other related tasks. The study provides supporting background material for construction of intelligent speech-based systems. Although the project presented in the paper is concerned with recognition of a command word for device control, this work provides supporting background for development of intelligent systems. Research has focused on several areas, including machine learning architecture and embedded intelligence, health care monitoring, speech processing, and intelligent assistive systems. Table 1 this section reviews the research papers in question and identifies and analyzes commonalities in their methodologies, application domains, and contributions.

Table 1. Literature Comparison

Domain	Research Focus	Summary
TinyML [1]	Machine learning for TinyML	Presented a survey of ML techniques, architectures, and optimization approaches for resource-constrained devices.
Speech Processing [2]	AI for speech classification and enhancement	Reviewed AI techniques for speech and language disorder classification and enhancement.
Healthcare / Assistive Technology [3]	Wearable intelligent throat	Presented a wearable system enabling natural speech support for stroke patients with dysarthria.
Rehabilitation Robotics [4]	Robotic hand rehabilitation	Reviewed the development, applications, and future potential of robotic hand rehabilitation systems.

Embedded AI / IoT [5]	MAX78000-based embedded AI	Investigated the implementation of embedded AI for IoT applications using a dedicated AI microcontroller.
Auditory Intelligence [6]	Multi-agent auditory scene analysis	Investigated inter-modular feedback for sound localization correction and speech quality improvement.
Accessible Education [7]	AI-driven multilingual XR services	Proposed integrating speech processing, translation, and sign-language rendering in immersive education environments.
Speech Processing [8]	SpeechPrompt	Introduced a prompting approach for applying speech language models to different speech processing tasks.
Automatic Speech Recognition [9]	Deep learning-based ASR	Reviewed deep learning architectures and techniques for automatic speech recognition.
Semantic Speech Analysis [10]	ML and DL for speech semantics	Reviewed machine learning and deep learning methods for extracting semantic information from speech.
TinyML [11]	Comprehensive TinyML survey	Reviewed TinyML architectures, hardware, optimization techniques, and application areas.
Healthcare Monitoring [12]	PPG-based blood pressure monitoring	Investigated a convolutional autoencoder for real-time blood pressure monitoring using TinyML.
Healthcare / Explainable AI [13]	Optimized TinyML and XAI	Explored energy-efficient fog-enabled healthcare decision support with explainable AI.
Smart Sensing / Chemical Analysis [14]	TinyML-Raman	Presented an IoT-based field-deployable spectroscopy approach for pharmaceutical and trace chemical identification.
Security / Embedded AI [15]	Trustworthy embedded ML	Investigated security, privacy, and trust in human-centric embedded machine learning.
Robotics / UAV [16]	Pedestrian tracking	Presented an onboard pedestrian tracking approach for nano-UAV platforms.
Edge AI / Speech [17]	Keyword spotting	Investigated on-device domain learning for keyword spotting on low-power embedded systems.
AI Security [18]	Quantized neural networks	Empirically evaluated attacks and defense approaches for quantized neural networks at the deep edge.
Wearable Sensing [19]	Eye tracking	Investigated infrared light sensing integrated into eyeglass lenses for invisible eye tracking.

IoT / Cybersecurity [20]	EV charging infrastructure	Examined TinyML cybersecurity issues and applications in electric vehicle charging infrastructure.

Various metrics are essential for assessment of the performance, reliability and efficiency of an AI system. Different application domains require different evaluation methods. The following table includes metrics that can be generally applied to evaluate the reviewed technologies. It is not being asserted that each of the listed papers reported each of the metrics.

Table 2. Evaluation Metrics Used Per Application Domain

Application Domain	Evaluation Metrics	Purpose
TinyML / Embedded AI [1], [5], [11]	Accuracy, latency, memory usage, model size, power consumption	Measures prediction performance and hardware efficiency.
Speech Recognition [8], [9]	Word Error Rate (WER), Character Error Rate (CER), accuracy	Measures speech recognition quality.
Speech Enhancement [2], [6]	PESQ, STOI, SNR, speech intelligibility	Evaluates speech quality and intelligibility.
Healthcare Monitoring [12], [13]	MAE, RMSE, MAPE, accuracy	Measures physiological prediction accuracy and decision performance.
Rehabilitation Robotics [4]	Range of motion, movement accuracy, task completion time	Evaluates rehabilitation performance and movement assistance.
Wearable Assistive Systems [3], [19]	Response time, accuracy, usability, reliability	Measures real-time operation and user experience.
UAV and Object Tracking [16]	Precision, recall, tracking accuracy, FPS	Evaluates object tracking and real-time performance.
Cybersecurity [15], [18], [20]	Attack success rate, detection rate, false positive rate	Measures system security and robustness.
Chemical / Smart Sensing [14]	Sensitivity, specificity, detection limit, classification accuracy	Evaluates chemical identification and sensing performance.
Accessible Education [7]	Translation accuracy, recognition accuracy, latency, usability	Measures accessibility and communication effectiveness.

4. RESEARCH GAPS

Important strides have been made in TinyML and EDGE/embedded Artificial Intelligence. However, research gaps still exist.

- TinyML models run on constrained and embedded systems with limited memory, processing power, and storage [1], [11].
- AI models consume more energy if they require continuous computation, which is a challenge in battery operated and small devices [5], [12].
- Background noise and other variations can affect recognition [2], [9], [10].
- Real-time health monitoring requires reliable sensors, models, and systems to ensure trustworthy decisions [12], [13].

- In healthcare, systems need to make explanations to end-users if the decisions are to affect their health and wellbeing [12], [13].
- AI and Edge Computing devices may be exposed to adversarial attacks, unauthorized access, and data leakages [15], [18], [20].
- Embedded and Edge devices have varying memory, processing and communication power [5], [11].
- Certain systems have not been evaluated in practical scenarios (various environments, users and operating conditions) [3], [4], [14].
- There are challenges integrating several sensors, AI models and Edge devices in a unified system [6], [7].
- Research is still needed to create unified systems that support multiple applications [1], [11].

5. Robustness in TinyML Framework

This figure 1 illustrates the major factors affecting the Robustness of TinyML (Tiny Machine Learning). Hardware constraints along with the application domains of TinyML systems are illustrated. Also shown are the evaluation metrics and how the categories of robustness impact the systems. This figure provides a broad level overview of the key factors influencing the development of robust TinyML systems. Taking into account hardware constraints, application domains, evaluation metrics, and categories of robustness, researchers can build machine learning models that are efficient, secure, reliable, and energy-aware, for various real-world IoT and embedded systems.

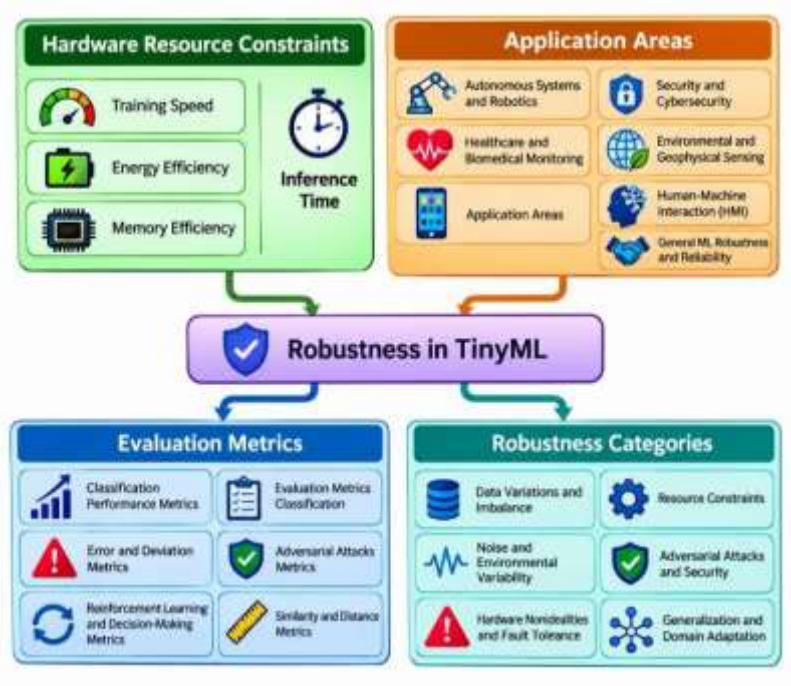


Figure 1: TinyML covers robustness through many aspects: categories, areas, constraints, and metrics of evaluation.

Figure 1 shows the key factors affecting the robustness and reliability of a TinyML system.

- **Hardware Resource Constraints:** Train and run speed, power consumption, and memory footprint.
- **Application Domains:** Robotics, cybersecurity, healthcare, environment sensing and interacting with humans.

- **Evaluation Methods:** Classify, measure errors, evaluate against adversarial examples, and calculate similarities.
- **Robustness Cases:** Data imbalance, resource constraints, environmental noises and attacks, hardware faults, and domain adaption.

6. CHALLENGES

The miniaturization of machine learning (TinyML) and the use of embedded artificial intelligence raise numerous complex technical and practical issues.

- **Computational Complexity:** The use of deep learning algorithms makes an additional burden on already constrained computing resources of low power microcontrollers.
- **Memory Constraints:** Embedded systems have very limited available RAM and flash for model execution and data.
- **Power Constraints:** Continuous sensor monitoring, and AI inference significantly increases the battery drain on the device.
- **Data Quality:** Sensor readings may be noisy and data may be incomplete.
- **Real-Time Processing:** Applications rely on low latency and fast response times.
- **Model Accuracy:** Quantization and pruning of a neural network may adversely affect prediction performance.
- **Threats to Security and Privacy:** Embedded devices may be attacked, or their data manipulated. Healthcare devices may process personal sensitive data.
- **Hardware Compatibility:** AI models may require modification to run across various embedded devices.
- **Environment:** Ambient conditions affect system performance.
- **Explainability:** It may not always be possible to explain or understand AI predictions.
- **Reliability and Practice:** Reliably moving from the lab to the real world requires extensive testing and engineering.

7. FUTURE RESEARCH DIRECTIONS

Future research should focus on maximizing the performance, reliability, accessibility and scalability of TinyML-based intelligent systems.

- **Developments in Model Compression:** Continue to improve the design of neural networks to make them smaller, while maintaining performance.
- **Energy Aware AI:** Continue research on new hardware accelerators and new techniques for performing AI inference.
- **Explainable TinyML:** Extend research on the integration of explainable AI techniques for embedded systems.
- **Privacy Preserving Learning:** Research new techniques for securely processing private data using local intelligence.
- **Speech Intelligence:** Continue research on the development of speech recognition and enhancement systems.
- **Healthcare Intelligence:** Continue research for predictive systems based on the integration of wearable sensors, TinyML and Physiological Intelligence.

- **Rehab Intelligence:** Continue research to develop an intelligent adaptive system for robotic rehabilitation.
- **Trusted Edge AI:** Research new systems for embedding intelligence in a trusted manner.
- **Multi-Sensor Integration:** Continue research to integrate multiple types of sensors for making reliable intelligent decisions.
- **Edge and Cloud Collaboration:** Continue research to integrate local intelligence with cloud-based systems for advanced analytics.
- **Long Term Testing:** Continue long-term research on embedded intelligence.
- Continue to integrate Speech, Language and AI for inclusive communication and education.

Table 3. Challenges and Corresponding Future Directions

Challenge	Future Directions
Limited computational resources	Develop lightweight neural network architectures.
High memory requirements	Apply model pruning and quantization.
High energy consumption	Use energy-efficient processors and inference techniques.
Low speech recognition accuracy	Develop noise-resistant and multilingual speech models.
Healthcare prediction errors	Improve sensor calibration and model validation.
Lack of explainability	Integrate Explainable AI techniques.
Security vulnerabilities	Implement secure authentication and adversarial defense.
Data privacy concerns	Explore federated and privacy-preserving learning.
Hardware compatibility	Develop hardware-independent model deployment frameworks.
Real-time processing delays	Optimize inference and edge processing pipelines.
Sensor data inconsistency	Apply multi-sensor fusion and data validation.
Limited real-world testing	Conduct long-term practical experiments.
Poor accessibility	Develop inclusive speech and assistive technologies.
Cloud dependency	Adopt hybrid edge-cloud AI architectures.
Limited scalability	Develop modular and interoperable embedded AI platforms.

8. CONCLUSION

This review surveys recent developments in the field of TinyML, embedded AI, speech recognition, intelligent sensing, and cybersecurity, as well as in healthcare, rehabilitation robotics, and wearable technologies. The reviewed studies show the value of TinyML in edge computing and reduce cloud dependency; improve the energy efficiency of intelligent edge systems and enable real-time processing. Efficient AI architectures provide a smaller “brain” for edge systems. The integration of speech and language processing and robotic systems in assistive technologies enables innovative solutions for intelligent assistance and services for the challenged and protected population. Alongside the inherent tradeoffs, especially the non-negligible energy consumption, reliability, privacy, and security of the

models remain important challenges. These challenges can partly be addressed through the integration of lightweight machine learning, explainable AI, IoT, and secure edge computing. There is a need to further integrate advanced AI architectures, fine-tune them for various edge systems, and ultimately realize them on energy-efficient hardware. Given the trends and the potential impact, it can be anticipated that the next generations of intelligent systems will leverage TinyML and embedded AI technologies.

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