A Systematic Literature Review of TinyML for Environmental Radiation Monitoring System

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Abstract. Tiny machine learning (TinyML) is an important and growing field, but academic research related to the term is still at a very early stage at this time. As a result, efforts to synthesize TinyML research into broad knowledge integration are relatively limited. Therefore, the development of tinyML in the environmental radiation monitoring system is carried out in stages and relies on the latest developments in tinyML technology. The application of TinyML for environmental radiation monitoring systems has not been used or has not been discovered in a published paper. To meet the needs of developing systems using tinyML, we started by conducting a systematic literature review (SLR). Until now there is no direct literature related to tinyML and environmental radiation monitoring systems, so SLR focuses on the literature on developing tinyML technology. The review results obtained are expected to meet the requirements and specifications of the developed system. In particular, this article contributes to the TinyML literature by synthesizing current research on the following aspects: scientific publication trends, hardware, and use case experiment sets. This review is carried out by selecting papers from journals and proceedings in scientific databases, namely Scopus, ScienceDirect, IEEE Xplore, and Web of Science. The process of selecting papers using special keyword strings for each database, using inclusion and exclusion criteria, and extracting data using Mendeley and Microsoft Excel. Paper selection resulted in 34 selected papers.

Keywords: TinyML · machine learning · systematic review · radiation monitoring

1 Introduction

Environmental radiation monitoring systems, especially around nuclear facilities, are needed to ensure the protection and safety of the public. An online radiation monitoring system that continuously detects the presence of radioactive material in the environment is an important system for the rapid detection of radioactive releases into the air. An IoT-Based Meteorological and Environmental Gamma Radiation Monitoring System

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have been developed and tested around the Nuclear Facility Engineering Center at the Serpong Nuclear Complex [1]. Furthermore, the system development uses machine learning to detect nuclear pollution in an open environment using the Support Vector Machine algorithm and Linear Discriminant Analysis [2].

Machine learning has become an indispensable part of the existing technology domain. Edge computing and the Internet of Things (IoT) together present new opportunities to imply machine learning techniques on resource-constrained embedded devices at the network edge. Conventional machine learning requires enormous power to predict scenarios. The TinyML (Tiny Machine Learning) paradigm aims to transform the majority from high-end traditional systems to low-end clients.

TinyML's goal is to apply machine learning inference to very low power (under one milliwatt) and low-cost microcontrollers (MCUs). Through the deployment of various battery-powered MCUs and streaming applications, TinyML facilitates real-time on-site data collection, processing, analysis, and interpretation [3]. TinyML is a fast-growing research area committed to democratizing deep learning for all-pervasive microcontrollers (MCUs). Challenged by the constraints on power, memory, and computation, TinyML has achieved significant advancement in the last few years [4]. The main obstacles currently hindering the growth of the TinyML paradigm are estimated to have four main aspects, minimum battery energy of 10–100 mAh, a processor clock speed of 10–1000 MHz, a memory of less than 1 MB, and cost [5].

2 Methodology

Literature studies related to TinyML for environmental radiation monitoring systems have used a systematic literature review method. A systematic literature review guide was first proposed by Kitchenham and Charters which identifies, assesses, and interprets all literature findings on a research topic to answer research questions (RQ) [6]. To evaluate and interpret all available research relevant to a particular research question, topic area, or phenomenon of interest requires a means of a systematic review. Systematic reviews aim to provide a fair evaluation of research topics using a reliable, rigorous, and auditable methodology. The need for systematic reviews arises from the need for researchers to summarize all available information about some phenomena in a comprehensive and unbiased manner. It is possible to draw general conclusions about some phenomena than is possible from individual studies, obtain information on the latest research status, or as a prelude to further research activities.

The purpose of the literature review paper related to tinyML is to get the latest status related to the development of tinyML applications to be applied in environmental radiation monitoring systems. For that, we need data related to the hardware used, available memory, power consumption, framework, and algorithms used. The results of this review will be used for the development of a radiation monitoring system using tinyML.

2.1 Research Questions

We identified three main research questions (RQ) about tinyML as follows: [7].

1. RQ 1: How many studies related to this research theme, publication trends, citation analysis, paper distribution, and geographic distribution were last published?
2. RQ 2: What are the applications of tinyML and the main components of microcontroller devices among published papers?
3. RQ 3: What is the scope of tinyML's future research for the development of environmental radiation monitoring systems?

2.2 Scientific Databases for Papers Searching (Search Process)

A literature review was conducted by collecting relevant papers on four scientific databases, which are Scopus, ScienceDirect, IEEE Xplore, and Web of Science. We selected only journals and proceeding conference was published during last 10 years and written in English.

2.3 Study Selection of Papers

At the time this paper was written, there was only one research paper we could find on the application of tinyML in radiation monitoring systems. This means that tinyML technology has not been widely used or published, so the search topic is focused on keywords: tinyML or tiny-ML or tiny machine learning. To search for papers in each database, a specific keyword string is used, as described below.

4. Scopus: https://www.scopus.com/search/form.uri#basic

   Keywords: (TITLE (tinyml) OR TITLE ("tiny-ml") OR TITLE ("tiny ml") OR TITLE ("tiny machine learning")

5. ScienceDirect: https://www.sciencedirect.com/

   Keywords: tinyml OR "tiny-ml" OR "tiny ml" OR "tiny machine learning"

6. IEEE Xplore: https://ieeexplore.ieee.org/Xplore/home.jsp

   Keywords: tinyml OR "tiny-ml" OR "tiny ml" OR "tiny machine learning"

7. Web of Science: https://www.webofscience.com/wos/woscc/basic-search

   Keywords: (tinyml OR "tiny-ml" OR "tiny ml" OR "tiny machine learning").

2.4 Inclusion and Exclusion Criteria

Inclusion Criteria:

8. Topic research should focus on TinyML, environmental monitoring, and low power
9. Research tinyML experimental applications or use cases

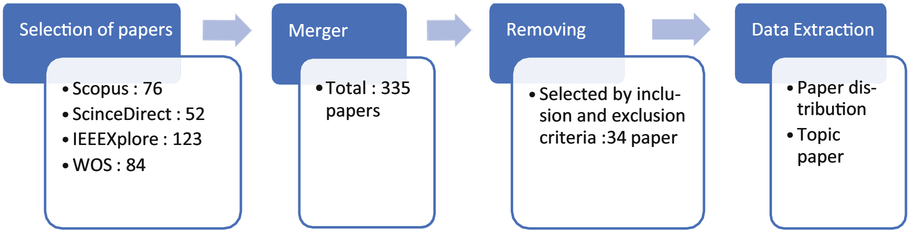


Fig. 1. Papers selection process

10. Uses marketed hardware and open source software
11. Papers published in four database journal (Scopus, ScienctDirect, IEEE Xplore and Web Of Science)
12. Papers published from 2012 until 2022 and written in English Exclusion criteria:

    a. Paper not related this topic research
    b. Duplicate papers
    c. Other article types such as books, encyclopedias, mini-reviews, and papers without full text (not open access)

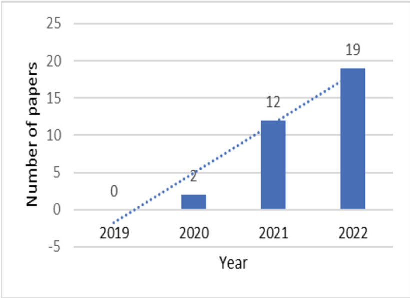
2.5 Data Extraction

Extract data by identifying the occurrence of certain words, topics, or concepts from the text in the paper. The aim is to integrate various studies into a conceptual map that describes the development of published papers (publishing trends, distribution, countries, citations) and the key elements of TinyML (hardware, use cases, frameworks, data sets, and algorithms/models) and directions for future development. We use Mendeley reference manager to manage and save selected documents. Data and information were recorded in Microsoft Excel for analysis.

3 Results and Discussion

To provide a more accountable insight, the selected studies only contained journal literature and proceedings, other publications were not included in the review. Publications are selected in two steps: first by reviewing the title, abstract, and keywords, then with a full-text review. The choice is not limited by the year of publication but papers must be written in English. All web-based resources can be accessed in print or download form.

Figure 1 shows the results of the initial literature search yielding 335 results. After reviewing titles, abstracts, and keywords, and deleting duplicates, we obtained 81 papers for further evaluation. After applying the inclusion and exclusion criteria while reading full-text, we obtained a final total of 34 papers (15 journals and 19 proceedings) used for data extraction.



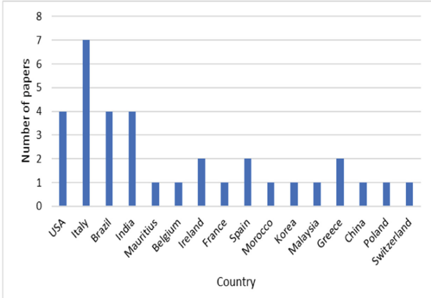


Fig. 2. Publication trend line (a) and author's country distribution of the paper publications (b)

3.1 Publication Trends and Author's Country Distribution of the Paper Publications

Figure 2 (a) shows the distribution of papers from 2019 to 2022. During the last 10 years, no paper related to tinyML was found before 2019. This is natural because tinyML technology was introduced in 2019 and is developing very quickly. Based on the publication trend, shows a very significant increase as technology is increasingly developed and many researchers are interested. Figure 2 (b) shows a graph of the author's country distribution of the paper publications. The data show that researchers are evenly distributed around the world. This shows that this technology was not developed by one country and shows the enthusiasm of many researchers around the world. Italy is the country with the most published papers. Almost all continents are also involved and actively contribute to the development of this tinyML technology.

3.2 Publication Papers Distribution Among Journals and Conferences

Studies on TinyML have been published in various journals and conferences. From 34 papers selected consisted of 15 papers were published in journals and 19 papers were published in conferences. Figure 3 (a) is the number of papers published at each conference. The research paper was published in 16 proceedings. Figure 3 (b) is the number of papers published in each journal. The research paper was published in 13 journals.

3.3 Citation Analysis

One method to assess the level of expertise of a researcher is by the number of papers produced and cited by other researchers. The more papers that are cited by other researchers, the more information from those papers is needed by others to conduct research. Scopus platform is used for citation analysis, used to analyze the number of citations in this review. Table 1 shows the top 5 papers cited for research on this topic. Miguel de Prado's paper entitled Robustifying the Deployment of tinyML Models for Autonomous mini-vehicles was cited by most of the other researchers with a total of 8 citations.

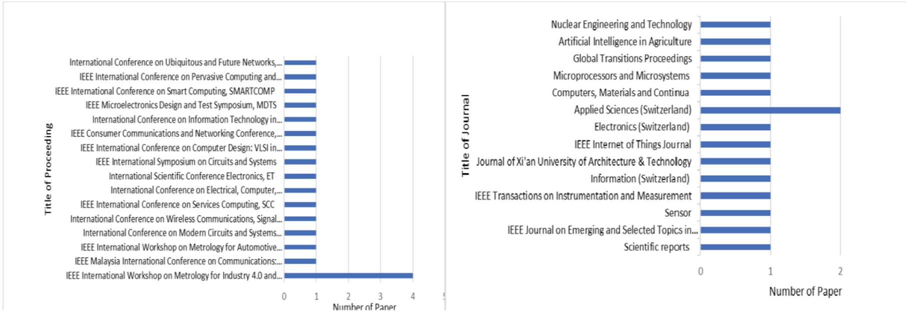


Fig. 3. Number of papers published in each proceeding (a) and number of papers published in each journal (b)

Table 1. Citation papers

Title papers	Year	Citations
Robustifying the Deployment of tinyML Models for Autonomous mini-vehicles	2021	8
An Unsupervised TinyML Approach Applied for Pavement Anomalies Detection Under the Internet of Intelligent Vehicles	2021	7
A TinyML Platform for On-Device Continual Learning with Quantized Latent Replays	2021	6
Adaptive Traffic Control with TinyML	2021	4
An SRAM Optimized Approach for Constant Memory Consumption and Ultra-fast Execution of ML Classifiers on TinyML Hardware	2021	4

3.4 Main Component of TinyML Among Papers Publication

TinyML is a combination of hardware and software, with very stringent hardware and software support. TinyML is a rapidly growing research area committed to democratizing deep learning for all-pervasive microcontrollers (MCUs). Challenged by power constraints, memory limitations, and computations, TinyML has made significant progress in recent years [5]. Currently, for tinyML hardware requirements, several microcontrollers are available in the market such as those used for experiments in several papers that have been reviewed. Table 2 shows some of the hardware and its specifications.

3.5 Use Case Themes in Research Publication

Although TinyML is still in its infancy, there are many use cases that apply TinyML to solving real-life problems. In this review, we identify use cases, such as anomaly detection in food supply chain security, fall detection for the elderly using sound technology, greenhouses temperature forecasting, support elderly care, autonomous driving

Table 2. Hardware platform to support tinyML

Hardware	Processor	CPU Clock (MHz)	Flash (MB)	SRAM (kB)	Power/Voltage	Connectivity	Sensor/Connector
Arduino Nano 33 [8–17]	Cortex M4 – nRF52840	64	1	256	3,3V, 15 mA/pin	UART, SPI, I2C, USB, BLE	IMU, microphone, gesture, light, proximity, barometer, temperature, humidity
STM32F Discovery [18–23]	32-bit ARM Cortex-M4 FPU Core	48 MHz	1 MB	192 KB	3–5 V	LQFP100 I/O, USB	Accelerometer, microphone,
Arduino Portenta H7 [24]	ARM Cortex-M7, ARM Cortex-M4 GPU	480 MHz, 240 MHz	16 MB	8 MB SDRAM	3.7–5 V, Li-Po cell, 700mAh	WiFi, BLE, 10/100 Ethernet Phy, USB, MIPI DSI, MPI D-PHY	Temperature, camera extension
Nordic Semi nRF52840 DK [18, 23, 25]	ARM Cortex M4	64 MHz	192 KB	24 KB	1.7–5 V Li-Po	BLE5,Bluetooth mesh, Thread, Zigbee,802.15.4, ANT, 2.4 GHz, NFC,UART	–
Raspberry Pi 4B [26–28]	64-bit ARM Cortex-A72 quad core, Broadcom BCM2711	1.5 GHz	–	256 KB	3.8–4 W, 3.3–5 V	WiFi, BLE, CSI, DSI, HDMI, USB, Ethernet	Temperature
ESP-32 [18, 23, 29, 29]	32-bit ESP32	240 MHz	4 MB	8 MB PSRAM	3.3 V	WiFi, USB, SPI, I2C, UART, BLE	2MP camera
ATSAMD51G19A [30]	32-bit ARM Cortex-M4F	120 MHz	1 MB	256 kB		UART, SPI, I2C, USB,	SiPM micro radiation sensor

mini-vehicles, environmental Predictions, and more. We added the use case “Technology Upgrade” as another type of use case. Table 3. Shows tinyML use case among paper publications.

Gamma Radiation Classifier

TinyML is implemented for automatic radiation detection and identification using a small low power gamma sensor as SiPM (Silicon Photo Multiplier). The TinyML model is designed using the Edge Impulse cloud platform, adopting a Convolutional Neural Network (CNN). Gamma source dataset provided by the International Atomic Energy Agency (IAEA), augmented using MATLAB software. To deploy the model on embedded devices, Edge Impulse offers deployment systems for multiple platforms. In our case, the ATSAMD51P microcontroller embedded in the WIO terminal was used. The deployment process includes an optimizer to reduce the amount of memory used by the program. All the libraries required by the model are also included [30].

Image Classification

The most popular and largely deployed case of TinyML is image classification.

Table 3. Use case TinyML among papers publications

Use Case	References
Gamma radiation classifier	[30]
Image classification	[24, 27, 31–34]
Gas detection	[13, 28, 29, 35]
Voice recognition	[10, 12, 20]
Activity detection	[26, 37–39]
Anomaly detection	[8, 11, 30]
Forecasting	[16, 22]
Motor control	[21, 40]
Threat prediction	[9]
Fingerprint classification	[40]
Technology upgrade	[15, 17, 18, 23, 37]

Researchers bring Smart farming to the agricultural ecosystem to increase its productivity. TinyML and LoRaWAN were used to propose an energy-efficient model capable of detecting fruit to demonstrate the technological capabilities in the agricultural domain to perform TinyML, a microcontroller equipped with a camera and a LoRaWan communication module [24]. A new non-destructive system for detecting ripeness and disease defects in tomatoes, using digital image processing techniques with a minimal number of features compared to existing systems [33]. In the case of farmland, an animal disturbance is a major threat to crop productivity, reducing profits for farmers and affecting food security. Raspberry cameras are used to capture images of intruders entering farmland. The images are analyzed with a machine learning algorithm running on a Raspberry pi board. Furthermore, conclusions are drawn as the output of the machine learning algorithm [27].

Gas Detection

Vehicles are the main source of air pollution in big cities. Improper vehicle conditions can result in excessive CO2 levels and produce harmful gases. Modern cars are equipped with multiple sensors, which offer the opportunity to develop algorithms that can monitor and diagnose vehicle performance more efficiently. TinyML is embedded into typical OBD-II automotive scanners to function as a soft sensor and estimate carbon dioxide emissions [35]. The adoption of embedded algorithms for mounting vehicles is a promising approach, which can significantly benefit smart city macro systems. As smart vehicles become interconnected, we can better understand how air pollution is generated and how public actions can be adopted to reduce its negative impact [29]. Another TinyML application is to detect hazardous gas leaks. The system can be trained to detect irregularities and notify occupants using BLE technology via messages sent to smartphones. This device can be installed in a household environment to warn occupants of fumes or gases such as Liquefied Petroleum Gas (LPG), when the system is placed in a garage. The system is based on TinyML BLE, creating an autonomous system that does not require an internet connection, access to the cloud for data processing and alerting, or communication with other devices [13].

Voice Recognition

TinyML can be implemented to classify words in audio data. To find words in raw audio data continuously requires pre-processing, unlike image classification. Audio recognition is an application that requires a lot of raw data pre-processing, but the network model used for classification cannot accept such large input data. Therefore, the features are extracted using several complex preprocessing steps [20]. The human voice can be recognized with this tinyML technology. Everyone has a different sound frequency, amplitude, and pronunciation time. Therefore, it is necessary to look for the unique characteristics of the target word in the voice data series. TinyML technology can be implemented to determine coarse age with speech recognition. Research has been carried out by building a TinyML dataset and a model for rough age classification based on voice commands. Data points undergo pre-processing by the Audacity app before being uploaded to the Edge Impulse platform for labeling [12].

Activity Detection

TinyML based optimized real-life solution applications are extensively developed. Human Activity Recognition (HAR) and fall detection have been hot research topics since the advent of IoT along with the integration of various types of low-cost sensors in smartphones and other everyday gadgets. The older we get, the weaker our physical strength becomes. The need for fall detection devices for the elderly is becoming increasingly important. A convolutional neural network model was developed and trained to study fall detection using voice technology so that the model can have autonomic recognition capabilities for elderly falls from other sounds [38]. Another paper proposes the use of accelerometer sensors in a non-invasive way to detect falls to support elderly care. Using deep learning edge, machine learning based detection system using BLE sensor network. Machine learning models can run in real-time on edge devices using Edge Impulse [25]. In the case of electric vehicles, by utilizing a connected personal mobility vehicle, a Machine Learning (ML)-based fall detection system is introduced on a new device that analyzes data taken from various sensors integrated into the On Board Unit (OBU) prototype [26].

Anomaly Detection

Performance Extreme industrial environments present harsh operating conditions and limited resources, which are further exacerbated by the reduced computing capabilities of most IoT devices. An ML-based anomaly detection system has been developed that uses retrofit kits based on limited and cost- effective IoT devices [29]. In the area of food supply chain security, anomaly detection systems can be developed to detect and report when abnormalities are found throughout the supply chain. This abnormality can be caused by a defective food product, incorrect operation of the machine, or an attempt to tamper with the monitoring device [8].

Forecasting

A statistical approach can be designed to perform weather forecasting activities using machine learning (ML) techniques. The recent growing interest in the Edge Computing Tiny Intelligent architecture suggests a shift towards implementing ML algorithms on Tiny Embedded Systems. Deep but Tiny Neural Networks (DTNN) can be designed to be cost-effective and can be automatically converted into STM32 microcontroller-optimized C libraries via the X-CUBE-AI toolchain [22]. Another approach using tinyML focuses on using machine learning (ML) algorithms to forecast greenhouse temperatures [16].

Motor Control

It has been developed utilizing the compact, high-throughput tinyCNN family to control the mini-vehicle, which learns in the target environment by imitating the expert's computer vision algorithm [21].

Threat Prediction

The increasing use of tinyML also poses a major challenge, namely security. To keep the security aspect guaranteed, it is necessary to implement a Cyber Threat Intelligence Platform on the Internet of Things (IoT) using the TinyML approach. In addition, if we design a threat prediction model using the TinyML platform, the integration in the microcontroller and subsequently in the smart device will be smoother and more energy efficient. A model has been designed based on a machine learning approach that uses a Naive Bayes classifier to extract potential threat intelligence from heterogeneous data sources and the model can predict threat incidents accurately [15].

Fingerprint Classification

Electrical loads are monitored by analyzing changes in voltage and current measured at the connection points of household power plugs. The idea is to use their unique fingerprint to identify and classify active equipment. This helps to separate the total power consumption and the individual power consumption [40].

Technology Upgrade

The topic of the paper is more towards improving tinyML technology than using tinyML technology in real life.

3.6 Future Research on the Development TinyML for Environmental Radiation Monitoring System

TinyML broadly covers the area of machine learning technologies that can be used to analyze sensor data on devices with very low power consumption. Between hardware advancements and the recent innovations of the TinyML community in the machine learning field, it is now possible to execute increasingly complex deep learning models (the basis for most modern applications of artificial intelligence) directly on the microcontroller.

The results of the review obtained from this SLR, there are several possibilities for the application of tinyML in the environmental radiation monitoring system. Aspects that can be developed are related to radiation counting systems, data transmission, and device management (anomaly detection).

The next study is the application of TinyML for environmental radiation monitoring systems, the system created requires handling with machine learning embedded in the microcontroller. Parts that require handling machine learning include radiation detection systems and device management systems. The machine learning method was chosen as the element analysis method because according to some literature it has a fast element detection rate with high accuracy. The monitoring station is installed independently and uses a solar panel power supply, so a device management system is needed that can detect any anomalies or malfunctions during the operation of the device. With the system to be developed, it is hoped that from the detection results, the system can report or repair itself on anomalies that occur.

4 Conclusions

TinyML is an important and rapidly growing field that requires interchange between various integral components (hardware, software, machine learning algorithms). In this paper, we contribute a systematic literature review that draws on the results of synthesizing data from 34 publications on TinyML since 2019. We focus on five elements: hardware, frameworks, data sets, use cases, and algorithms/models. From the results of this literature review, there is a possibility that tinyML can be used to be applied to the environmental radiation monitoring system that will be developed. Furthermore, the selection of hardware and algorithms to be used can be done.

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