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Review Article

Application of Tiny Machine Learning in Predicative Maintenance in Industries

Samson O. Ooko [1,2,*] and Simon M. Karume [2]

[1] School of Postgraduate Studies, Adventist University of Africa, Nairobi, Kenya; e-mail: ookosoft@gmail.com
[2] School of Science, Engineering and Technology, Kabarak University, Nakuru, Kenya;
e-mail; ookosam@kabarak.ac.ke ; skarume@kabarak.ac.ke
* Corresponding Author: Samson O. Ooko

Abstract: The advancements in the Internet of Things (IoT) and Machine Learning (ML) have enabled significant improvements in Predictive Maintenance (PdM) in industries, providing economic benefits by reducing equipment downtime and maintenance costs. Traditional ML approaches, however, require more computational resources and are often limited to cloud-based processing, leading to increased costs and high latencies. Tiny Machine Learning (TinyML) offers a novel solution by enabling ML models to run on low-power, resource-constrained devices at the edge, facilitating real-time, on-device inference. This review analyzes TinyML applications in PdM, highlighting the technology's potential to transform industrial maintenance practices. We explore the differences between TinyML and standard ML, discuss the economic and operational advantages of adopting PdM, and present practical case studies where TinyML has been successfully implemented. In addition, we address the challenges facing TinyML, including hardware limitations and the need for specialized algorithms. Our findings indicate that while TinyML is a promising technology for PdM, further research is needed to overcome these challenges and fully realize its potential. This review contributes to understanding TinyML's role in industrial PdM and outlines a roadmap for future research and development in this emerging field.

Keywords: Edge AI; Industrial Applications; Machine Learning; TinyML; Predictive Maintenance.

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1. Introduction

The emerging fields of the Internet of Things (IoT) [1] and Artificial Intelligence (AI) [2], [3] are increasingly being used in different domains, including industrial applications [4]. Developing cost-effective solutions involving embedded systems is a major approach for enabling real-time responses and efficiency in industrial automation. Such embedded systems, based on Microcontroller Units (MCUs), have received growing attention due to their size, cost, and low energy consumption, making them ideal for designing monitoring solutions in the industrial sector [5]. These solutions frequently incorporate AI functionalities to enable real-time predictions and intelligent monitoring [6], [7].

Given the resource constraints of embedded devices, they cannot process the needed resource-intensive AI algorithms. Therefore, the data collected by such devices is often sent to the cloud for processing, with the results being sent back to the device for action or notifications. However, cloud-based implementations also need significant computational load to process large amounts of raw data from each IoT device. Additionally, the rate at which data is transferred from the edge devices to the cloud and vice versa often acts as a limiting factor, especially where real-time responses are required [5]. There is thus a need for the development of cost-effective and robust machine learning algorithms tailored for IoT devices with limited resources, leading to the increasing popularity of Tiny Machine Learning, often referred to as TinyML [8].

TinyML represents an evolution in machine learning aimed at extending ML capabilities to edge devices, particularly ultra-low-power devices operating under a milliwatt [9]. Unlike standard ML, which often relies on powerful cloud servers, TinyML enables ML inference

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directly on microcontroller devices[10]. By processing data on-device and close to sensors, TinyML enhances responsiveness and privacy, significantly reducing the energy consumption associated with wireless data transmission—a notable improvement over traditional approaches where transmission costs are higher than computational costs at this scale. This shift towards tiny, energy-efficient ML models on edge devices marks a significant evolution in the field, pushing beyond mobile inference toward greater autonomy, efficiency, and functionality in edge systems [10].

Recent studies, as presented in a review by [11], show the importance of predictive maintenance (PdM) in the context of Industry 4.0 [12]. PdM enhances manufacturing process performance and efficiency by predicting equipment failures before they occur, thereby increasing equipment lifespan, minimizing downtime, and reducing repair costs. This supports sustainable operational management [13]. The continued use of IoT and integration with machine learning has made this a reality [14]–[16]. However, as [17] identifies, several challenges exist in implementing predictive maintenance, such as financial and organizational constraints, data source limitations, machine repair activity challenges, and difficulties in deploying industrial predictive maintenance models. Additionally, [18] outlines the challenge of IoT infrastructure and data management, emphasizing the importance of smart data over merely large volumes of data for predictive maintenance. Further, [18] highlights the need for simpler and more affordable implementations of predictive maintenance systems, even for small and medium-sized companies.

TinyML is suggested by [17] as a promising solution to some of these challenges, enabling intelligent predictive maintenance strategies through embedded, low-power machine learning algorithms that can process data directly on the device. This approach potentially addresses the gap in deploying predictive maintenance models by reducing reliance on large-scale data infrastructure and overcoming some of the data source and computational limitations. TinyML enables edge devices to process and interpret data on-site, significantly reducing the need for extensive data transmission and storage [19]. It enhances the efficiency and dependability of IoT systems by ensuring that only relevant, actionable insights are communicated back to the central system, thus optimizing infrastructure usage and improving the reliability of predictive maintenance outcomes.

In industrial settings, quickly identifying anomalies is essential for minimizing repair downtimes, enhancing production efficiency, and reducing costs [20], [21]. Implementing TinyML directly on devices allows for ongoing monitoring and analysis of sounds produced by machinery during operation, providing early warnings of potential failures without the need for connectivity—a common challenge in industrial environments. By examining parameters such as sound or vibration in real-time, industries can expedite diagnosing and addressing equipment problems, thereby avoiding unwarranted delays in maintenance or replacement, ultimately saving time and maintaining continuous operations[22].

However, [22] notes a gap in the literature and research concerning the use of TinyML techniques in industrial applications. Moreover, based on a review of existing literature up to February 2024, no single study focused on this area. This study thus presents a systematic literature review on TinyML and its application in predictive maintenance within industries, highlighting the existing challenges and opportunities. It aims to serve as a guide for researchers exploring the application of TinyML in predictive maintenance.

The main contributions of this study include a) A comprehensive and systematic literature review focusing specifically on applying TinyML in predictive maintenance for industrial applications. This fills a gap in the literature by offering an in-depth examination of how TinyML can be tailored for predictive maintenance tasks, which has not been extensively reviewed in previous studies. b) The proposal of a specific process flow for TinyML applications in predictive maintenance. This proposed process flow serves as a guide for implementing TinyML-driven predictive maintenance solutions. c) A classification of use cases and applications, providing valuable insights into the current state of ML and TinyML applications in industrial settings and identifying areas where TinyML can be further exploited for predictive maintenance. d) Identify existing challenges in deploying TinyML for predictive maintenance and highlight opportunities, paving the way for future research and development.

The rest of the paper is organized as follows: the next section presents the literature review, followed by the research methodology, the results, and the discussion, and after that, the conclusion is drawn.

2. Literature Review

2.1. Predictive Maintenance

Current methodologies, architectures, and technologies that support PdM applications are presented in [11], [12], [23], [24]. The studies presented gaps such as the lack of standardization and the difficulty in implementation. In addition, the reviewed studies present limitations, including the focus on maintenance monitoring models without adequately addressing predictive aspects. The studies suggest several future research directions to advance the field of PdM within Industry 4.0. These include developing autonomous monitoring systems with predictive alerts, embracing multidisciplinary approaches for intelligent maintenance, addressing the challenges of data volume and testing challenges, utilizing image and thermographic data for maintenance, and integrating additional processes within the industrial ecosystem.

The advancement of predictive maintenance within the framework of Industry 4.0, presenting a platform designed for industrial predictive maintenance based on asset management and intelligent maintenance planning, has been presented in [17]. This platform and the one presented in [25] integrate various types of sensors and maintenance approaches, supporting real-time on-site PdM across different types of machinery and equipment. Such solutions enable maintenance management and decision-making through data-driven models and allow for the manipulation and modification of maintenance plans by users and maintenance teams with different access levels.

Moreover, the solutions in [26], enable mobile and web connections for real-time monitoring and notifications through a dashboard that calculates key performance indicators and supports API protocols for data customization. Such approaches are significant because they move beyond the application of maintenance 4.0, as presented in [27], which has traditionally focused on specific machines or equipment, towards a comprehensive, user-friendly platform that supports diverse industrial assets, as also applied in [28].

These solutions apply smart algorithms and maintenance models, enhancing operational efficiency, safety, and cost savings by minimizing downtime. However, the studies highlight the challenges and future directions for intelligent predictive maintenance projects, emphasizing the importance of modeling, simulation, experimental validation, system instrumentation, data processing, and cybersecurity. The adoption of intelligent predictive maintenance is thus increasingly recognized as a priority in manufacturing sectors, underscoring the potential of Maintenance 4.0 [13] to transform industrial maintenance routines.

2.2 Machine Learning in Predictive Maintenance

Studies on the application of Machine Learning (ML) [29] techniques in Predictive Maintenance [25] highlight the emerging intersection of these fields, especially in the context of Industry 4.0 advancements as presented in [30]–[35]. The studies reveal that while PdM strategies are increasingly achievable and promise to improve maintenance processes, challenges remain in standardizing and comparing different ML approaches across specific equipment types. A key insight is the specificity of ML applications to particular types of equipment, which complicates the comparative analysis of different ML techniques in PdM [36]. Despite this, the integration of ML in PdM is acknowledged for its potential to reduce costs, enhance safety, and improve the availability and efficiency of industrial processes by enabling the avoidance of unnecessary equipment replacements [4]. From the review, it was noted that standard ML methods are reliant on extensive parameter tuning, which is attributed to the increasing exploration of PdM by industrial experts. It underlines the importance of having foundational Ready to Fail and Preventive Maintenance strategies in place for effective data collection, which is important for designing and validating PdM strategies.

The reviewed literature presents the application of various ML techniques, including Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANN), Deep Learning, and k-means clustering, in developing PdM solutions [37]. Despite these advances, the studies identify several areas requiring further research: Development of advanced sensing techniques to enhance data quality and quantity, enabling more effective PdM applications; Comparative studies of different ML algorithms in PdM strategies to broaden understanding and optimization of ML applications in this field; Exploration of novel ML algorithms and ensemble learning methods to achieve more robust and accurate predictions in

PdM applications; and Creation and dissemination of new datasets to facilitate benchmarking and innovation in PdM research [4], [30], [38].

This study is an initial step to address the identified gaps in current research. Using TinyML improves data processing efficiency and model deployment in resource-constrained environments. This approach not only promises to enhance the scalability and accessibility of PdM solutions across various industries but also contributes to the ongoing dialogue on optimizing ML integration for maintenance strategies. The application of TinyML in predictive maintenance will set a new benchmark for cost-effective, efficient, and scalable PdM solutions.

2.3 TinyML in Predictive Maintenance

The emerging field of Tiny Machine Learning (TinyML) represents a significant shift in the landscape of artificial intelligence (AI), promising to address some of the most pressing challenges associated with conventional AI technologies [8]. As AI increasingly integrates into various aspects of our lives, concerns regarding its extensive computational demands, high costs, energy consumption, and consequent environmental impacts have become more pronounced[25]. TinyML emerges as a transformative solution to these challenges, enabling the deployment of AI models on low-power, cost-effective hardware with a minimal environmental footprint [10]. The reviewed studies emphasize TinyML's potential to catalyze sustainable development across diverse sectors such as healthcare, smart agriculture, environmental monitoring, and anomaly detection[39].

A notable aspect of TinyML is its capacity to significantly reduce latency and facilitate real-time data processing at the source, eliminating the need for constant internet connectivity [5]. This capability not only enhances the efficiency of AI applications but also strengthens user privacy and data security. The reviewed studies present a comprehensive taxonomy of TinyML techniques and their innovative applications, offering new insights into how TinyML is unlocking sustainable development avenues, as presented in [8]. However, the studies also identify ongoing challenges and call for future research directions, emphasizing the need for further innovation in TinyML methodologies, applications, and hardware optimization. A comprehensive literature review of TinyML has been presented, emphasizing its significance and rapid development in integrating hardware, software, and machine learning algorithms [39]. It suggests that future research could broaden the scope to include additional application areas such as Industry 4.0, vehicular services, smart spaces, agriculture, and eHealth. TinyML is positioned as a transformative force capable of opening up new domains for smart applications across various sectors, offering innovative solutions and directions for further academic exploration.

These insights affirm the novelty and significance of investigating TinyML's potential in this domain as is explored in this study, it will not only illustrate TinyML's broad applicability and benefits across various sectors but also specifically highlight its relevance and promise in enhancing predictive maintenance strategies. By presenting a review on integrating TinyML into predictive maintenance, the study aims to contribute to developing more efficient, cost-effective, and environmentally friendly maintenance solutions, aligning with the overarching goals of sustainable development and technological innovation in the era of Industry 4.0. The study will significantly enrich the existing body of knowledge and serve as a valuable addition to existing findings.

3. Research Method

A Systematic Literature Review (SLR) was used in the study. This methodology is used in software engineering to identify, evaluate, and interpret relevant parts of research on specific areas or issues of interest [40]. The SLR consisted of the following steps: defining research questions, identifying research, selecting studies, extracting data, and synthesizing and reporting.

3.1. Research Questions (RQs)

The scope of this review was guided by answering the following questions four questions;

RQ 1. How is Machine Learning applied in predictive maintenance?

RQ 2. Are there applications that apply TinyML for predictive maintenance in industries, and what are their limitations?

RQ 3. What are the existing challenges in applying TinyML in industries, and what are the directions for future research?

The research questions addressed gaps in the current understanding of TinyML's capabilities and challenges in industrial PdM applications. Specifically, they aim to explore the practical implementation of TinyML, the economic benefits, and the existing technological and infrastructural challenges. These questions are critical for guiding future research and development in this field, ensuring that the most pressing issues are addressed;

3.2 Search Strategy

After formulating the research questions, the researchers defined the search string and databases. Google Scholar was selected as a starting database due to the ability to perform free searches in publications and texts. The aim was to find a high volume of text at the beginning to help in refining the search string before applying in SCOPUS indexed databases, which included but were not limited to IEEE, Elsevier, Springer, MDPI, Emerald, SAGE, ACM, and Taylor and Francis. The search strings used were as follows;

- Tiny Machine Learning AND Predictive Maintenance
- Machine Learning AND Predictive Maintenance
- Predictive Maintenance AND Industries
- Tiny Machine Learning AND Industries
- Machine Learning AND Industries

3.3 Article Selection

The search strings were applied to the selected databases as of February 21, 2024, with a filter considering the last 10 years, 2014-2024, and removing quotations and patents. The articles were then exported to Zotero software[41]. The total number of articles downloaded was 252. The quality assessment criteria, presented in Table 1, were used to filter the articles further to ensure only the most relevant ones were reviewed.

Table 1. Quality Assessment Criteria.

Section	Description
Criteria 1	Exclude any article published before 2014
Criteria 2	Exclude books, thesis, and technical reports.
Criteria 3	Exclude publications that are less than three pages long and not in English.
Criteria 4	Exclude publications that do not use the search terms in the title, abstract, conclusion, or keywords.
Criteria 5	Exclude publications that are duplicates.

After applying the quality assessment criteria, 164 articles were selected for data extraction and analysis.

3.4 Article Selection Results

3.4.1 Type of paper

Most of the selected articles were journal papers. Figure 1 presents the percentage of reviewed journal articles compared to conference papers.

3.4.2 Year of publication

The publications selected show a rising trend over the years. However, a decline in 2023 is not conclusive as it may be attributed to the limited availability of online papers for conferences held later in the year. Interestingly, no papers were selected that had been published in 2016. It will be interesting to investigate the reason for this. Figure 2 shows a plot of the year of publications for the selected papers

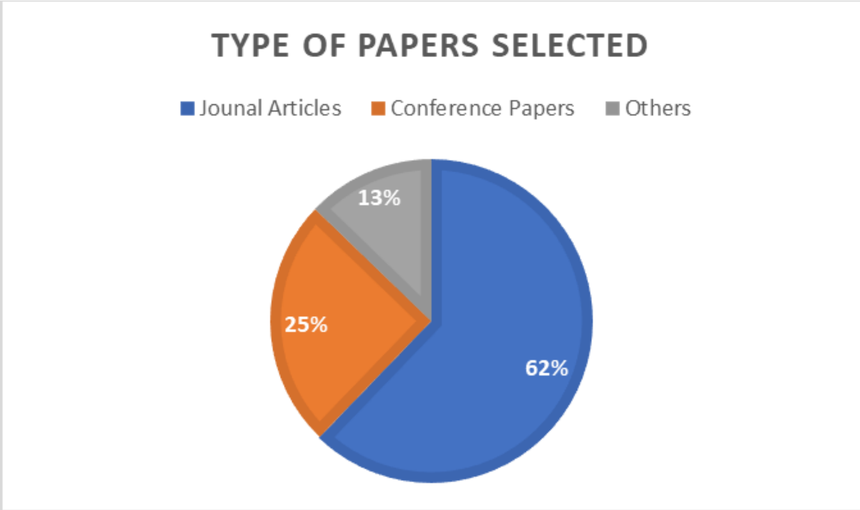

Figure 1. Type of Papers selected for review

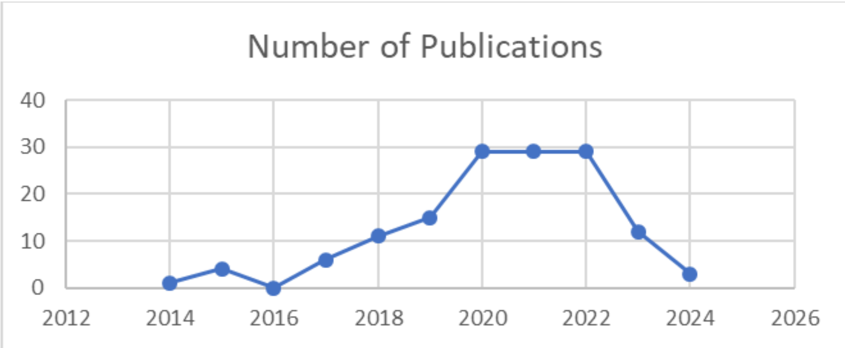

Figure 2. Year of Publications for the selected papers

3.4.3 Area of Focus

Most publications focused on using traditional ML architectures in PdM applications, with those focused on TinyML or Edge implementations just beginning to emerge. Figure 3 presents a comparison of the two areas of focus.

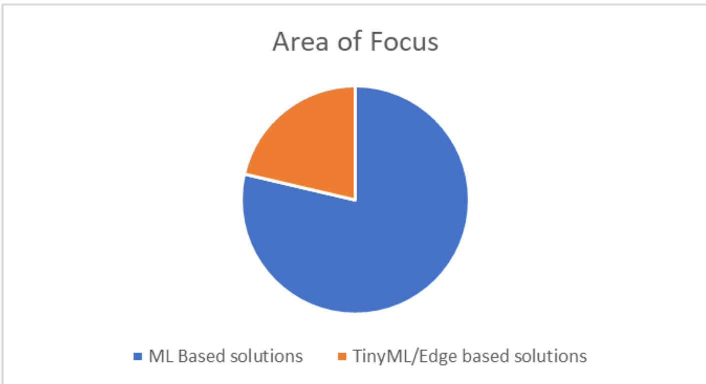

Figure 3. Areas of focus for the selected papers

4. Results and Discussion

4.1. Machine Learning in Predictive Maintenance

Predictive maintenance is a proactive approach used across industries to anticipate and address equipment issues before they lead to failures [33], [42]. This strategy is key for enhancing operational efficiency, reducing unplanned downtime, and saving costs [43]. Unlike reactive maintenance, which responds to equipment failure after the fact, or preventive maintenance, which schedules maintenance at regular intervals regardless of need, predictive maintenance utilizes real-time data and condition monitoring to predict when maintenance should be performed [44]. The study [45] highlights implementing machine learning techniques as an effective solution for preventive maintenance planning, emphasizing its potential to reduce corrective maintenance expenses by 13% for 2020. This approach significantly improves equipment reliability and operational uptime [46].

Predictive maintenance represents a strategic approach within industrial maintenance to enhance productivity by preventing equipment failures before they occur[47], [48]. This strategy has evolved significantly with the advent of Industry 4.0 technologies, shifting from reactive and preventive maintenance towards a more intelligent, data-driven methodology that leverages real-time data analysis to foresee and prevent equipment failures [49], [50]. The integration of technologies such as the Internet of Things (IoT), machine learning, and augmented reality (AR) into predictive maintenance systems has enabled more sophisticated monitoring and analysis capabilities, facilitating the transition from traditional maintenance practices to more proactive and efficient strategies[51]–[54].

The rise of Industry 4.0 has revolutionized predictive maintenance through the integration of advanced technologies such as machine learning (ML) and artificial intelligence (AI) [55], [56]. In the realm of predictive maintenance, machine learning plays a crucial role by offering the capability to predict the likelihood of equipment failure before it occurs[57]. This approach relies on analyzing vast amounts of data from various sources, such as tool sensors, process parameters, and historical maintenance records. Applying machine learning algorithms to these data sets makes it possible to identify patterns and trends that precede equipment failures. This predictive capability allows for maintenance to be scheduled at an optimal time before the equipment fails but not so early that it leads to unnecessary downtime or wasteful use of resources[58]. Such a strategy not only enhances the reliability and availability of the equipment but also significantly reduces maintenance costs and operational efficiency [52].

These technologies analyze data from sensors attached to equipment to detect patterns indicative of potential failures. Machine learning algorithms, including convolutional neural networks (CNN), long short-term memory (LSTM) networks, and deep learning models, are particularly effective in processing and analyzing this data. They can predict equipment failures and estimate machinery's Remaining Useful Life (RUL), allowing maintenance teams to schedule interventions precisely and avoid unnecessary maintenance actions or unexpected breakdowns [17]. Such applications can be classified as presented in Figure 4.

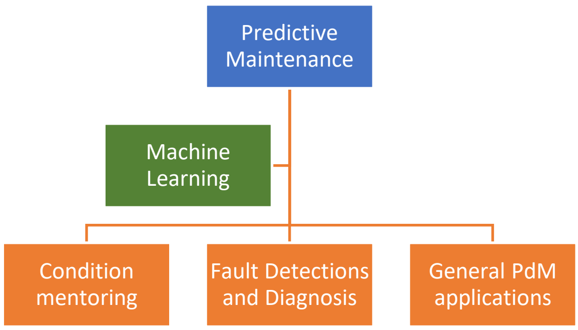

Figure 4. Classification of ML applications in PdM.

Condition monitoring applications include monitoring the health of centrifugal compressors [17], monitoring different industrial equipment in real-time, monitoring the real-time condition of bearings [59], and predicting machine conditions [60]. Fault detection and diagnosis applications include early fault detection in predictive maintenance [61], fault diagnosis in manufacturing environments [62], and prediction of the possibility of failure in semiconductor manufacturing [52]. Wind turbine fault diagnosis and predictive maintenance[64], diagnostic systems of heavy machinery, such as agricultural equipment, to predict failures and guide maintenance decisions effectively[65], fault analysis and predictive maintenance of induction motors[66], predicting bearing failures [67], predicting the time-to-failure of industrial machines [68], system modeling for anomaly detection and predictive maintenance within industrial settings [69], anomaly detection in vessel engines[70].

General Applications include Maintenance for Electrical Submersible Pumps (ESPs) in the petroleum industry[71], Aircraft predictive maintenance [72], Predictive maintenance for distribution transformers [45], Predictive maintenance of a metallic stamping machine [51], Optimizing dynamic flow-shop production scheduling[73], Predictive maintenance framework for building installations [74], an industrial metal stamping machine [53], a woodworking cutting machine[75], [76]. Predictive maintenance planning framework for MEP components [77]. Predictive maintenance in oil and gas equipment[78], a predictive maintenance framework for nuclear infrastructure[79], and predictive maintenance in the shipping industry [80]. Predictive maintenance (PdM) in machining processes[81], maintenance within the greek railways[82], motor classification [83], predictive maintenance of a slitting machine [84], Predictive maintenance framework for ballast pumps in ship repair yards [85], predictive maintenance for industrial packaging robots [86], predicting the operational accuracy of industrial machines, specifically within a cement production plant [87], predictive maintenance system for industrial equipment monitoring, [88], predictive maintenance for industrial radial fans [89].

While the predictive maintenance models demonstrate the potential of machine learning to transform maintenance strategies, their application in the context of Tiny ML or small-scale industries is constrained by data availability, computational resource requirements, expertise, implementation costs, and the need for model customization. Addressing these limitations requires innovative solutions, such as developing more efficient machine learning algorithms, enhancing data collection practices, and fostering collaborations to share knowledge and resources.

4.2 TinyML in Predictive Maintenance

4.2.1 TinyML and Its Evolution

TinyML represents a significant growth in AI, prioritizing deploying machine learning models on devices with minimal power consumption, such as microcontrollers and embedded systems[90]. Created to mitigate AI's environmental impact and make it more accessible, TinyML introduces an innovation where intelligence is pushed to the edge, enabling AI processing on devices far smaller and more power-efficient than traditional computing devices[91].

The inception of IoT in 1999 laid the stepping stone for a network extending beyond computers to include more tiny devices, thereby setting the stage for integrating machine learning into these devices to make them smarter [92]. As the IoT ecosystem expanded, cloud computing's limitations became clear, leading to the emergence of Fog computing and, subsequently, Edge AI. These developments sought to bring processing closer to data sources, reducing latency and enhancing faster and real-time decision-making. TinyML is the culmination of these advancements, inspired by Mobile ML's efficiency and driven by breakthroughs in IoT and microcontroller technology[93]. TinyML has found applications across different sectors, including healthcare, agriculture, and industrial IoT, presenting its versatility and broad applicability[8]. Different models and frameworks, such as the TinyMLOps framework systems[94] introduce a specialized approach for implementing Ma-chine Learning (ML) models in resource-constrained Internet of Things (IoT) devices, also known as far-edge devices.

4.2.2 TinyML vs. Standard ML

TinyML and standard ML differ primarily in their computational environments. Standard ML typically operates in cloud or high-performance computing environments, leveraging substantial computational power and data storage capabilities. In contrast, TinyML is designed for edge devices with limited power and computational resources, such as microcontrollers.

The strengths of TinyML include the following: TinyML models are optimized for power efficiency, making them ideal for battery-operated devices; By processing data on-device, TinyML reduces the latency associated with data transmission to and from cloud servers; Data is processed locally, minimizing the risk of data breaches during transmission. On the other hand, the weaknesses of TinyML include the following: TinyML devices cannot handle as complex models as those used in standard ML, which can limit the sophistication of the algorithms. To fit within the memory constraints of edge devices, TinyML models are often simplified, which can affect their accuracy and performance.

The strengths of Standard ML, however, are that Standard ML can handle complex models and large datasets, leading to potentially higher accuracy and more advanced applications; Cloud-based infrastructures can scale resources dynamically, accommodating varying workloads. In addition, the weaknesses of Standard ML include High Latency and Power Consumption: The need to transmit data to centralized servers can introduce latency and require significant power. Transmitting data over networks can pose security risks.

4.2.3 Benefits of TinyML

Real-Time Applications: By minimizing latency, TinyML facilitates deploying applications like image and speech recognition directly at the data source, enabling faster response times critical in real-time decision-making scenarios.

Privacy and Security Enhancements: With data processing confined to the device, TinyML significantly boosts user privacy and complies with different data protection regulations, addressing a growing concern in AI ethics.

Low Energy Consumption: TinyML devices consume substantially less power than traditional computing hardware, allowing for extended battery power operation and contributing to a greener, more sustainable technology landscape.

Cost-Effectiveness: By processing data locally, TinyML reduces the need for data transmission to cloud servers, saving on bandwidth and storage costs and lowering energy consumption costs.

4.2.4 Proposed TinyML Process Flow

The TinyML process begins with the collection of data from various sources, including data from humans, computerized systems, different IoT-driven/embedded devices, and synthetic data generators. After data collection, different algorithms are applied to train the data through supervised or unsupervised learning. The training may begin from scratch or build on existing trained models through transfer, reinforcement, or federated learning. The training is normally done on cloud-based systems with the needed computational resources. After training, the model is optimized for deployment on tiny edge devices, where inference takes place as an application. Figure 5 presents the proposed TinyML process flow.

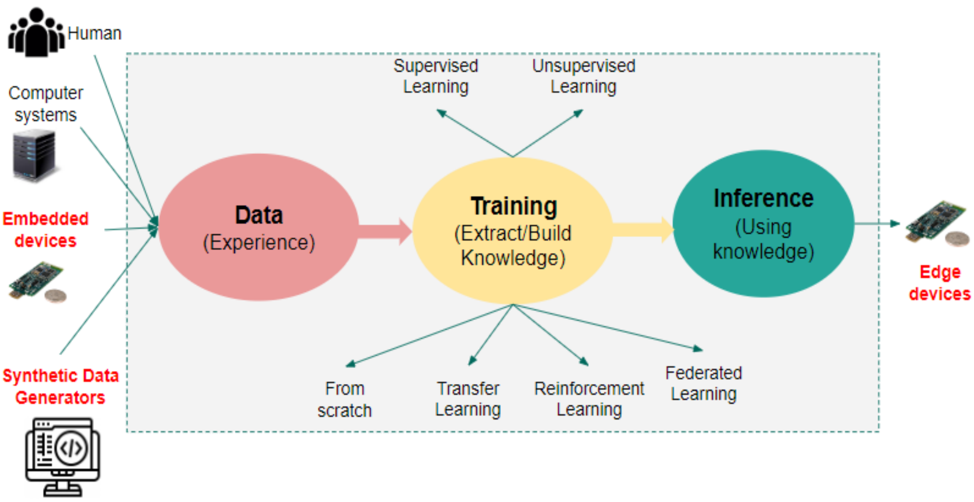

Figure 5. Proposed TinyML process flow

4.2.5 Applicability in Predictive Maintenance

In the industrial sector, predictive maintenance is a critical area where TinyML can profoundly impact. By embedding ML algorithms at the edge, manufacturers can continuously monitor and analyze machine output—such as sounds, temperature, movements, or vibrations—to detect anomalies indicative of potential failures. This real-time analysis can significantly reduce downtime by allowing for prompt corrective actions, enhancing overall production efficiency and reducing maintenance costs.

4.3 TinyML Use Cases in Industrial PdM

This section presents recent studies that leverage TinyML for Predictive Maintenance (PdM) across various sectors. The studies are classified according to their specific tasks, such as anomaly detection, health and condition monitoring, operational monitoring and analysis, and predictive maintenance. This task-based categorization aims to provide a clear and structured overview of how TinyML is being utilized to revolutionize predictive maintenance practices, highlighting the unique approaches and solutions developed to tackle different challenges within industrial settings.

4.3.1 Anomaly Detection

These studies focus on identifying unusual patterns that do not conform to expected behavior. To begin with, a study developed a TinyML model deployed on an STM32H743Z12 microcontroller unit (MCU) for anomaly detection in rotating machinery. The system uses an accelerometer to acquire vibration signals, processes these to extract features, and employs an autoencoder ML model for local training and inference, achieving real-time anomaly detection with high efficiency[95]. Another study described a system for detecting anomalies in submersible pumps at wastewater plants using an ESP32DEVKIT MCU with sensors for temperature and vibration. The system utilizes an Isolation Forest model for edge-based anomaly detection, demonstrating the feasibility of retrofitting existing equipment with TinyML capabilities [96].

An innovative sensor system that utilizes three microcontroller unit (MCU)--based TinyML cameras designed for automatic artifact and anomaly detection in plastic components is proposed. This system integrates a top camera for identifying shape defects and two side cameras for detecting color anomalies, with the entire data processing executed locally on TinyML, significantly reducing data transmission needs. The study evaluates two state-of-the-art convolutional neural network (CNN) architectures, MobileNetV2 and SqueezeNet, for their suitability in resource-constrained microcontrollers, focusing on their ability to maintain high classification accuracy (99%) and real-time performance with minimal energy consumption[90].

In addition, an Auto-Encoder model for anomaly detection in time-series vibration sensor data, tailored for deployment on resource-constrained embedded hardware, specifically an ARM Cortex-M4 microcontroller, has also been proposed. The model stands out for its minimal footprint (7.5 KB) and demonstrates promising results with accuracy and precision around 80%, despite the inherent trade-offs between model size and accuracy due to post-training quantization[63]. A TinyML model running on an ESP-WROOM-32 MCU device was created to detect anomalies in thermal images of machinery. By leveraging a convolutional neural network (CNN) and sending data via MQTT only upon anomaly detection, this approach exemplifies TinyML's potential to reduce data transmission needs and enhance maintenance efficiency[97].

Moreover, a framework was applied to an anomaly detection scenario involving industrial rotary machines. A validation scenario within a wastewater management plant demonstrates the framework's feasibility. It involves emulating sensor data production using the NASA Bearing Dataset and implementing the anomaly detection system on an ESP32 microcontroller for the edge device and a Raspberry Pi 4B as the gateway[94]. Last but not least, a study presents an innovative anomaly detection system designed for extreme industrial environments, leveraging the synergy of IoT, edge computing, and TinyML. Using the isolation forest algorithm, it employs an ESP32 microcontroller-based IoT kit for real-time data processing and anomaly detection. It demonstrates efficient performance with quick inference times and minimal memory requirements. Incorporating blockchain technology for data integrity [98].

4.3.2 Operational Monitoring and Analysis

Include applications that continuously monitor for operational efficiency, safety, or specific conditions indicative of the need for intervention. First, a study presents a predictive maintenance approach for industrial applications, particularly in the textile industry, focusing on circular knitting machines. The approach integrates the Internet of Things (IoT) and machine learning (ML) technologies, leveraging a system of IoT-enabled devices to monitor machine operations in real-time. Data on machine speeds and stops are collected, preprocessed, and analyzed using the AdaBoost machine learning algorithm [99]. Another study presents a comprehensive analysis of the use of thermal, mechanical, and partial discharge sensors to monitor critical grid assets continuously. By employing machine learning algorithms, these sensor data can be analyzed to predict equipment failures, thereby enabling timely maintenance interventions[100]. An application of TinyML for real-time impact localization on thin plastic plates using low-power, resource-constrained IoT devices has been presented. Leveraging piezoelectric sensor data and implementing machine learning models, specifically Random Forest and Shallow Neural Networks, on an Arduino NANO 33 BLE microcontroller [92].

Further, an article introduces an ultralow-power Smart IoT device designed to monitor the activity of handheld power tools in construction environments, leveraging Tiny Machine Learning (TinyML) for edge processing. It uniquely categorizes tool usage into various operational modes (transport, no-load, metal drilling, and wood drilling), facilitating optimized maintenance, extended tool lifecycles, and improved safety. Utilizing Bluetooth Low Energy (BLE) and Near Field Communication (NFC) for efficient data communication and activation, the device incorporates temperature, humidity, and acceleration sensors [101].

4.3.3 Health and Condition Monitoring

Involves assessing the health or condition of equipment to identify maintenance needs or operational adjustments. To begin with, a study introduces a pioneering TinyML approach for non-repudiable anomaly detection within extreme industrial settings, focusing on a retrofitting kit designed for condition monitoring (CM) of industrial assets such as pumps in wastewater management plants. This IoT-based solution is equipped with sensors and a microcontroller unit (MCU) to process and analyze data locally, employing an unsupervised anomaly detection algorithm for real-time monitoring. The integration of TinyML facilitates the autonomous learning of normal operational patterns directly on constrained devices, optimizing the detection process without external dependencies. Additionally, the system harnesses blockchain technology to create a secure, immutable log of detected anomalies, enhancing the transparency and reliability of the maintenance process [96].

A study has been presented to address the challenge of deploying Deep Neural Network (DNN) models on Microcontroller Units (MCUs) for predictive maintenance, particularly focusing on bearing health prediction in rotating machinery. The paper explores methods to overcome these limitations, such as pruning and quantization, to reduce model size without significantly compromising accuracy[101]. In addition, a study explores the deployment of machine learning algorithms on an embedded microcontroller for real-time anomaly detection in mechanical systems, specifically a top-load washing machine. The study focuses on detecting unbalanced loads during the washing cycle by collecting and analyzing accelerometer data from normal (balanced) and abnormal (unbalanced) laundry loads. Two types of neural network models, an autoencoder and a variational autoencoder (VAE), were trained using the normal dataset and then deployed on an Arduino Nano microcontroller attached to the washing machine[102].

4.3.4 Predictive Maintenance

Aimed at predicting when maintenance should be performed to prevent failure, enhance operational efficiency, and extend equipment lifespan. First, a study introduces a novel Low-Power On-Device Predictive Maintenance (LOPdM) system that incorporates Self-Powered Sensing (SPS) and Tiny Machine Learning (TinyML) to offer high-precision, energy-efficient equipment failure predictions directly on the device. Leveraging a lightweight piezoelectric cantilever for sensing and analyzing data through advanced AI models, specifically Random Forest (RF) and Deep Neural Network (DNN), the system achieves up to 99% accuracy in detecting anomalies with minimal data requirements[103]–[105]. In addition, a paper discusses an initiative by the INFN-CNAF computing center to implement a predictive maintenance system using machine learning to analyze complex and unstructured log data from services like StoRM, a Grid Storage Resource Manager[106]. A Deep Echo State Network (DeepESN) model was proposed for monitoring water distribution systems capable of adapting to environmental changes. This online learning anomaly detection model demonstrates TinyML's flexibility and applicability in critical infrastructure maintenance [107].

Further, a Block based Binary Shallow Echo State Network (BBS-ESN) model was proposed. This model emphasizes TinyML's capacity for handling complex tasks like im-age-based anomaly detection through deep quantization techniques, highlighting its applicability in renewable energy sectors. In addition, a study [108] presents the use of machine learning for predictive maintenance in oil and gas industries.

A predictive maintenance system was developed for manufacturing production lines using machine learning models and real-time IoT sensor data. The aim was to predict potential equipment failures to prevent production stops. The system's effectiveness was validated with real-world data from a diaper production line, highlighting the significant performance of ensemble methods like Random Forest and XGBoost [109]. Also, a study explored the application of Tiny Machine Learning (TinyML) techniques for predicting the Remaining Useful Life (RUL) of turbofan engines, focusing on deployment in resource-constrained environments such as IoT devices. Utilizing the C-MAPSS dataset from NASA and deploying on an STM32F767ZI microcontroller with the X-CUBE-AI tool, the research evaluated various machine learning models, including Long Short-Term Memory networks (LSTM), Convolutional Neural Networks (CNN), XGBoost, and Random Forest [22].

Moreover, a study introduces a data-centric approach to enhance wind turbines' predictive maintenance (PdM). Utilizing a dataset provided by Energias De Portugal (EDP) and focusing on optimizing data preprocessing and feature selection rather than model complexity, the research demonstrates significant improvements in the prediction of Remaining Useful Life (RUL) for wind turbine components [110]. Another study introduces a novel real-time prediction method for estimating equipment's Remaining Useful Life (RUL) through a compact, efficient TinyML framework. Leveraging a two-dimensional Convolutional Neural Network (CNN) enhanced by L1 norm weight pruning and Adam optimization algorithm retraining, this method reduces the model's computational demands and memory footprint without significantly compromising accuracy. Tested on the C-MAPSS dataset from NASA, which contains diverse engine operation data, the proposed approach demonstrates its effectiveness in predictive maintenance applications [111].

In a comparative study, two IoT-based predictive analytics models, TinyLSTM and TinyModel from Edge Impulse, were evaluated for their effectiveness in on-device predictive maintenance through real-time prediction of industrial equipment's remaining useful life (RUL). The dataset comprised real-time data from critical components of an autoclave sterilizer, including Temperature, Vibration, and Current from two sources [112]. An innovative Edge AI system utilizing a thermal camera for industrial anomaly detection, focusing on predictive maintenance to minimize long-term costs and downtime, has also been proposed. This system employs deep neural networks (DNNs) to directly analyze temperature patterns indicative of machine conditions on microcontrollers, significantly reducing data transmission requirements [97]. Another study introduces an unsupervised on-device learning algorithm utilizing Tiny Machine Learning (TinyML) for anomaly detection, inspired by the extreme value theory. The methodology employs the two-parameter Weibull distribution function for identifying anomalies within discrete time series data, achieving impressive results in terms of accuracy (99.80%), recall (93.10%), and F1 score (96.43%) [113].

4.4. Analysis and Discussion

From the reviewed use cases, the development of TinyML models for PdM began in 2019, with a significant rise noted in 2022 as more applications emerged. The results show fewer applications in 2023 in this area of study, which can be attributed to the low availability of papers accepted online towards the end of 2023. The number of applications is still way below the numbers for cloud-based applications. In addition, many use cases remain unexploited, especially applications for small-scale industries. Figure 6 plots the use cases by the years of publication.

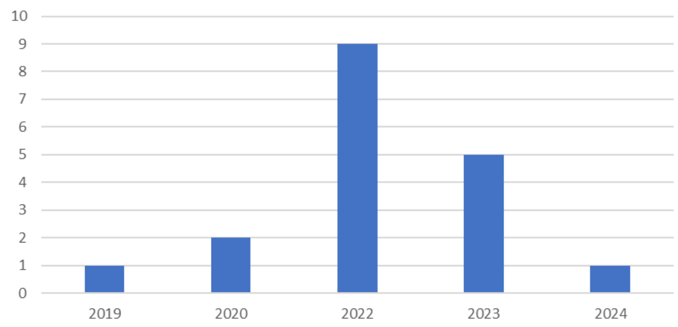

Figure 6. Number of Published TinyML-driven PdM use cases

4.4.1 Use Case Classification By Industry Sector

The applications can be classified based on the specific industry sector they are applied to. This can provide insights into how TinyML technologies are applied across different fields. Based on this classification, the reviewed use cases can be classified as;

- Manufacturing: Applications involving rotary machines, submersible pumps, and production lines.
- Energy: Use cases focused on wind turbines, water distribution systems, and grid asset monitoring.
- Construction: Monitoring of handheld power tools.
- Computing and Data Centers: Maintenance of computing infrastructure.
- Textile: Monitoring operations of circular knitting machines.

4.4.2 Use Case Classification By Sensor Type

Focusing on the type of sensors employed in each application reveals the diverse data sources TinyML models can work with;

- Vibration and Accelerometer Sensors: Rotating machinery, submersible pumps, wind turbine oil leak detection.
- Thermal and Temperature Sensors: Thermal anomaly detection in machinery, submersible pumps.
- Piezoelectric Sensors: Impact localization on thin plastic plates.
- Camera and Image Sensors: Plastic component inspection, wind turbine oil leak detection.
- Sound sensors

4.4.3 Use Case Classification By Task Type

Looking at the tasks TinyML models are performing offers insight into the common challenges addressed in industrial settings.

- Anomaly and Fault Detection: Most applications aim to identify unusual patterns that indicate potential failures.
- Predictive Maintenance: Applications focused on predicting when maintenance should be performed to prevent failure.
- Monitoring and Operation Analysis: Tasks that involve continuous monitoring for operational efficiency and safety.
- Health and Condition Monitoring: This involves assessing the health or condition of equipment to identify maintenance needs or operational adjustments.

Figure 7 presents a mind map of the application of TinyML in PdM in industries and will guide future studies.

Recent studies collectively demonstrate the transformative impact of TinyML in various Industry 4.0 applications, from manufacturing to energy systems and beyond. By integrating advanced machine learning algorithms on low-power Microcontroller Units the studies show the significant potential of TinyML in enhancing efficiency, optimizing resource allocation, and revolutionizing condition monitoring systems through real-time anomaly detection and predictive maintenance. An autoencoder model showcased remarkable performance in industrial anomaly detection with high accuracy and minimal impact on battery life, illustrating the feasibility of embedding complex ML algorithms in tiny IoT devices for early detection of mechanical failures and structural health monitoring. These studies support TinyML's important role in enabling scalable, efficient, and intelligent monitoring solutions, setting a significant precedent for future research in smart objects and the next generation of IoT solutions with minimal resource requirements, reduced latencies, and high accuracies.

4.5 Challenges in TinyML for Industrial Predictive Maintenance

The application of TinyML in industrial contexts faces numerous challenges:

1. Lack of a Benchmark for TinyML solutions: Developing a benchmark is a significant challenge due to the differences in TinyML workloads and hardware. The diversity in power consumption, computational capabilities, and memory constraints among devices complicates the creation of a universal benchmark.

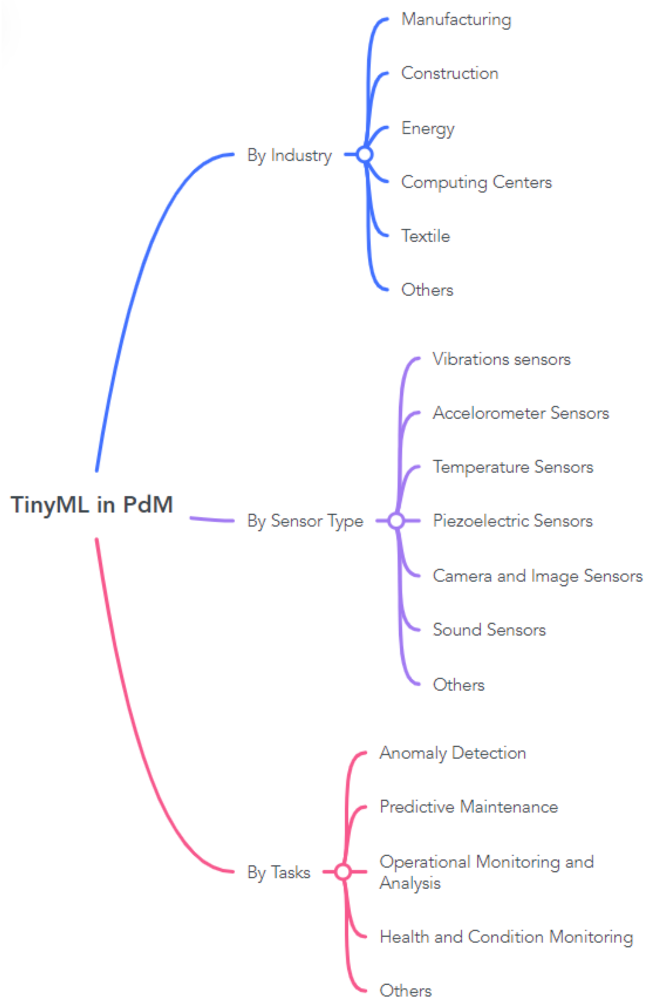

Figure 7. A mind map of TinyML in PdM use cases

2. Hardware and Software Heterogeneity: Addressing hardware and software heterogeneity is complex since TinyML systems can range from general-purpose microcontrollers to specialized low-power inference engines, and the software can vary from hand-coded models to those deployed via machine learning interpreters. This diversity hinders performance comparison.
3. Lack of standard models: Another challenge is selecting representative use cases and models due to the nascent stage of TinyML, which lacks consensus on standard models or use cases for benchmarks. Furthermore, achieving a balance between optimality, portability, and comparability of benchmarks is difficult but crucial for their meaningful adoption.
4. Limited memory: The iterative improvement of benchmarks is necessitated by the rapid evolution of TinyML, which requires adaptable benchmarks and is open to revisions. The limited memory of TinyML devices presents a significant challenge, necessitating trade-offs between model performance and memory usage.
5. Accuracy Drops: Deploying ML models on edge devices often results in decreased accuracy due to limited computational resources and data storage capacity.
6. Privacy issues: Privacy concerns arise from collecting potentially sensitive information by sensors.
7. Trustworthiness and reliability: The newness of TinyML and its application in critical domains, like healthcare, brings into question the trustworthiness and reliability of such devices.

4.6 Future Directions for TinyML in Industrial Predictive Maintenance

To overcome these challenges, several future directions are proposed. Establishing a common benchmarking framework that considers the unique characteristics of TinyML devices could enable fair comparisons and foster innovation. Embracing hardware and software diversity through open and closed divisions in benchmarking could include a broad range of TinyML solutions while ensuring comparability. Focusing on diversity in use cases and models for benchmarks could ensure they reflect the breadth of TinyML applications. Developing a benchmark suite with multiple deployment options could ensure the flexibility and adaptability of benchmarks to various TinyML systems.

Adopting an iterative approach to benchmark development could allow for refinement and expansion as the field evolves. Moving towards on-device learning could address the challenge of concept drift by allowing TinyML devices to adapt to environmental changes through real-time data updates. Utilizing memory optimization techniques such as compression and quantization could optimize memory usage without sacrificing model accuracy. Addressing privacy with embedded architecture could enhance the privacy and security of sensitive data. Lastly, ensuring the reliability and trustworthiness of TinyML devices through robust design and testing methodologies is crucial, especially in critical sectors.

These future directions offer a roadmap for addressing current limitations and unlocking the full potential of TinyML in industrial predictive maintenance and beyond, paving the way for innovative applications and advancements in the field.

5. Summary of Findings

We summarize the key findings of our review, noting that while TinyML is still in its early stages, it shows great promise for PdM applications. The technology's ability to operate on low-power devices makes it ideal for real-time monitoring and anomaly detection. However, practical implementation in the industry remains limited, highlighting a need for more case studies and practical examples. The review also identifies significant gaps in the literature, including a lack of standardized benchmarks and limited discussion on the scalability of TinyML solutions.

6. Study Limitations

The primary limitation of this study is the focus on specific industries, which may not be generalizable to all sectors. Additionally, the scope of the literature review was limited to English-language publications, potentially excluding relevant studies in other languages. Future research should consider a broader range of industries and include a more diverse set of studies to provide a comprehensive view of TinyML's applications and limitations.

7. Conclusions

This study underscores the transformative potential of Tiny Machine Learning (TinyML) in the realm of industrial predictive maintenance, illustrating its pivotal role in advancing maintenance strategies to be more aligned with the demands of Industry 4.0. Through a comprehensive literature review, the study reveals a growing interest in leveraging TinyML to enhance operational efficiency, reduce downtime, and ensure sustainable practices within industrial settings. It highlights the innovative application of TinyML in various sectors, demonstrating its versatility and effectiveness in real-time anomaly detection, health and condition monitoring, and operational analysis. However, the study also identifies significant challenges, including the need for benchmark development, hardware and software heterogeneity, memory constraints, and concerns regarding device reliability and data privacy. Addressing these challenges requires a concerted effort from researchers, practitioners, and industry stakeholders to develop a common benchmarking framework, adopt memory optimization techniques, and ensure the privacy and reliability of TinyML devices. The future of TinyML in industrial predictive maintenance is promising, with potential advancements in on-device learning, privacy-enhancing technologies, and the development of more reliable and diverse TinyML solutions. As the field continues to evolve, ongoing research and collaboration are crucial to unlocking the full potential of TinyML, driving forward predictive maintenance capabilities, and fostering a new era of industrial efficiency and sustainability.

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