



TinyML-Based Intelligent Plant Disease Detection for Low-Power Agricultural IoT Devices

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Abstract

Tiny Machine Learning (TinyML) is a promising way of integrating real-time, low-power Artificial Intelligence (AI) in resource-poor agricultural contexts. The present study reviews the recent advances in smart agriculture using TinyML in plant disease and pest detection, precision irrigation, UAV based agriculture, weed classification and sensor data processing. A structured literature analysis was performed with 23 representative studies published from 2023 to 2026 including lightweight deep learning, transfer learning, knowledge distillation, attention mechanisms, edge computing, IoT integration and adaptive model optimization. Based on the reviewed studies, we can conclude that TinyML can enable precise and timely decisions in agriculture, while minimizing computational demands, communication latency, energy usage, and reliance on cloud-based platforms. Applications such as crop disease and pest recognition, weed detection, irrigation monitoring and UAV-based field analysis have good potential for real-time implementation on microcontrollers and low-power edge devices. The results additionally reveal that model compression, optimized architectures and domain adaptation are significant for sustaining reliable performance with restricted RAM and processing sources. In conclusion, while TinyML offers a scalable and energy-efficient solution for precision agriculture, there are still several obstacles to overcome, such as training the models to be generalizable, hardware constraints, variability of datasets, data security, and field testing across a large number of deployments.

Keywords:

TinyML; Smart Agriculture; Edge AI; Plant Disease Detection; Precision Irrigation; Internet of Things

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1. Introduction

Artificial Intelligence (AI), Internet of Things (IoT) and edge computing are being increasingly used in agriculture to aid and advance crop monitoring, disease detection, irrigation and resource utilization. But the traditional cloud-based AI systems face challenges such as the need for constant internet connectivity, significant computational power, and bandwidth demands, making them less suitable for rural and resource-challenged farming settings. To overcome these challenges, Tiny Machine Learning (TinyML) has emerged to bring machine learning models directly to the microcontrollers and embedded devices with minimal power consumption. It shows high precision of localized inference, low latency and energy consumption, which is suitable for smart agriculture application [1]. An intelligent processing towards the source of the data generation thanks to the TinyML approach in precision agriculture. Lightweight models can be deployed at the edge devices, allowing them to do the analysis without sending a large amount of data to the cloud servers to do an analysis. Recent research in drone-based precision agriculture has shown the potential of the optimized TinyML models with adaptive path planning to enhance the autonomous agricultural monitoring [2]. Similarly, TinyML techniques have been explored for plant disease detection on agricultural crops like apple and mango, showing the potential of implementing efficient AI models on low-resource devices [3]. The possibility of using attention mechanisms with TinyML for ultra-low power agricultural sensor processing for real-time decision making has also been investigated, where less energy is used to process sensors [4].

Another key research direction is the creation of adaptable and transferable TinyML models for various agricultural settings. When there are differences in various aspects of crop varieties, environmental conditions, imaging devices, and disease characteristics between deployment locations, domain adaptation can enhance model usability. Overall, broader studies of TinyML applications highlight its promise to embedded intelligence, and outline challenges to limited memory, processing power, available energy, model optimization, and to scalability and deployment to larger numbers of systems. In other low-power embedded intelligent systems, the need for efficient architectures and hardware-aware optimisation for real world TinyML deployment is also noted [7]. One of the most promising areas for agricultural TinyML is plant disease detection, where early detection can aid in timely interventions and minimize crop losses. Recent implementation of IoT-based TinyML system has been reported on the rice leaf disease detection for real-time monitoring in agricultural environments, which demonstrates the potential of embedded intelligence to continuously monitor a real-time process within real-world challenges [8]. The need for intelligent agricultural technologies to reach small-scale, resource-limited farms has also been highlighted as an opportunity for low-power edge computing with artificial intelligence that is affordable [9]. The use of automated classification for the early detection of crop threats is also illustrated in machine learning applications that detect pests [10]. This is of special significance in areas where there is poor internet access and/or the computing power may not be available.

TinyML has also been used in a specific application to plant disease detection in resource limited communities, which shows its potential in supporting localised plant agricultural decision-making [11]. Another example of implementing a crop specific diagnostic system using constrained computing platforms is the lightweight models for bean crop disease classification [12]. Meanwhile, various TinyML application areas have been studied, where key considerations for sustainable deployment have been identified as model size, energy efficiency, computational complexity, privacy, security, and generalization [13]. TinyML and IoT can thus enable autonomous agricultural systems that can continuously sense, locally infer, and quickly respond [14]. In addition to disease and pest monitoring, machine learning is playing a crucial role in precision agriculture and crop management, such as in the detection, prediction, and automated decision-making [15]. In the context of precision irrigation, tinyML-based solutions rely on lightweight models to process vegetation and environmental information, helping to efficiently assess the status of the crops without wasting water [16]. In addition, the emergence of specialized TinyML devices and development tools facilitates the application of embedded AI systems in the field of agriculture [17]. The feasibility of TinyML has also been shown in resource-

constrained communities for detecting plant diseases and pests where traditional computing systems are constrained [18].

New advancements have been made in TinyML applications that include weed classification, UAV-based monitoring, and smart irrigation. Knowledge-distillation-based edge frameworks enable knowledge transfer from bigger models to smaller ones that are appropriate for IoT devices and are used for efficient weed classification under limited computational resources constraints [19]. TinyML enabled intelligent edge devices offers a wider technological bedrock for local AI inference and lesser reliance on centralized computing [20]. The potential of autonomous water management using continuous sensing and local decision making is also seen in sustainable precision irrigation systems, further evidence of the role TinyML and IoT can play [21]. Furthermore, TinyML has been explored for energy-efficient IoT security, suggesting that lightweight intelligence is also a potential solution to ensure the security of distributed agricultural devices and communication networks [22]. The potential of integrating both transfer learning and TinyML is also exemplified in the context of smart farming, where UAV-based solutions are employed to facilitate effective aerial monitoring in agriculture at the edge [23].

Notwithstanding these developments, there are still some hurdles to overcome before TinyML can be a complete, scalable solution for smart agriculture. The reliability of systems may be impacted by variability in field conditions, limited and imbalanced datasets, hardware limitations, model accuracy, availability of energy, connectivity, security, and laboratory versus field environments. As a result, it is crucial to have an extensive evaluation of existing TinyML approaches and their practical feasibility for agricultural implementation. The present study presents the overview of recent research efforts related to Tiny-ML in smart agriculture, especially plant disease and pest detection, precision irrigation, UAV based monitoring, weed classification, edge intelligence and integration of Tiny-ML with IoT. The goal is to characterize the main methodological trends, advantages, constraints, and research directions of innovative farm systems that are accurate, energy efficient, affordable, and scalable, featuring TinyML.

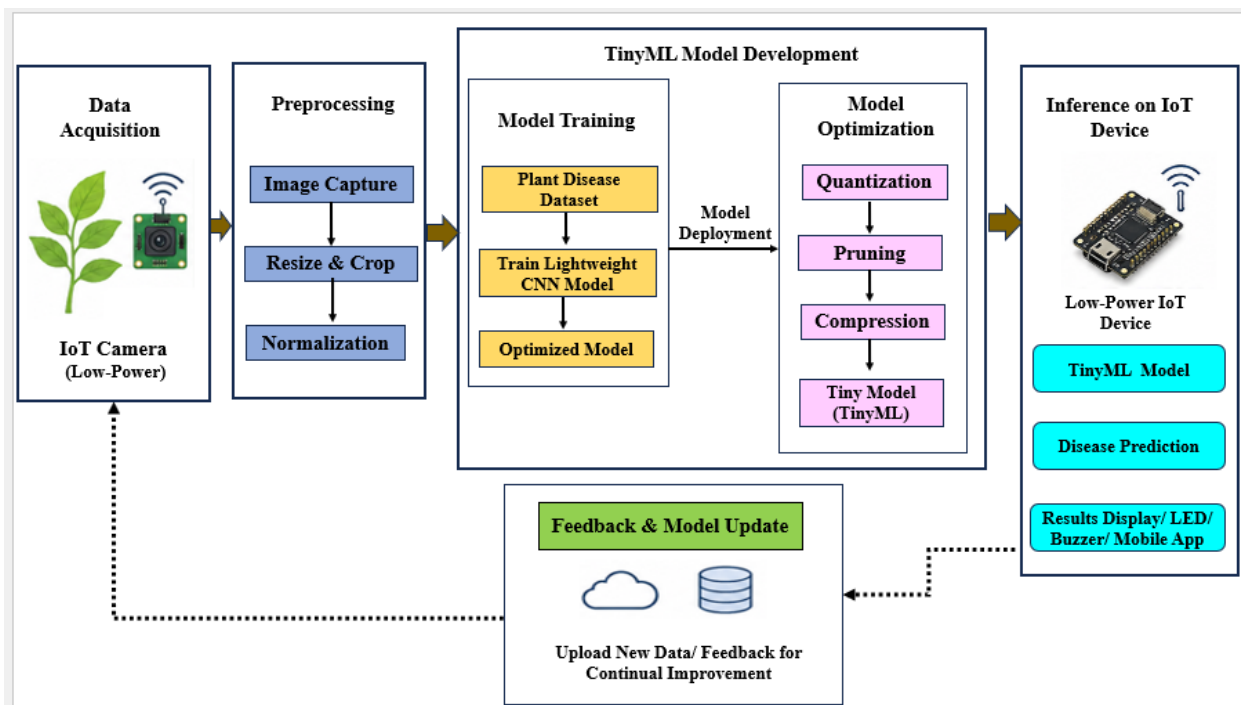


Fig. 1. TinyML-Based Intelligent Plant Disease Detection System for Low-Power Agricultural IoT Devices

Fig. 1. illustrates the complete workflow of a TinyML-based plant disease detection system designed for low-power agricultural IoT devices. First, plant images are captured using a low-power IoT camera. The acquired images undergo preprocessing, including image capture, resizing, cropping, and normalization. The processed data are then used to train a lightweight CNN model using a plant disease dataset. The trained model is optimized through quantization, pruning, and compression to create a compact TinyML model. This model is deployed on a low-power IoT device for real-time disease prediction and result display through an LED, buzzer, or mobile application. Feedback and new data are subsequently used for continuous model improvement and updating.

2. Literature Survey

Recent studies have shown that TinyML is an effective paradigm to make AI closer to the data sources in agriculture, especially when it comes to limited computational resources, energy, and connectivity. Lightweight machine learning, hardware-aware optimization, and on-device inference were identified as critical approaches to address the challenges of constrained environments through a comprehensive survey of TinyML [1]. The combination of optimized TinyML models and UAVs and adaptive path planning has been used to facilitate efficient field monitoring in the field of precision agriculture [2]. The lightweight deep learning approach has also been used to detect leaf diseases of apple and mango, and the feasibility of real-time crop diagnosis on edge hardware was demonstrated [3]. Additionally, attention-based TinyML architectures have been explored for low-power agricultural sensor processing for better intelligent analysis in the local microcontroller [4]. The issue of distribution differences between the training set and deployment set has been explored for domain-adaptive TinyML in detecting pest and disease in varying agriculture environments [5].

There have been several studies that have been concentrated on crop disease, pest and weed detection. The rice leaf disease identification system with tinyML has been successfully verified by deploying an edge device equipped with the Internet of Things (IoT) [8]. Low-cost and low-power deployment has also been highlighted for resource poor agricultural communities with affordable edge AI and TinyML frameworks [9]. AI-based early pest detection methods are a basis for automated identification of threats for crops and decision support [10]. The idea of deploying tinyML for the detection of plant diseases has been explored in resource constrained communities in West Africa, where the objective is to perform local inference without reliance on cloud infrastructure [11]. In addition, lightweight TinyML models have been developed to classify bean crop diseases, making the diagnosis of diseases in constrained devices possible [12]. These capabilities have been expanded to classify weeds using knowledge-distillation techniques, whereby the knowledge is transferred from a larger model to a smaller one at the edge [19].

The scope of TinyML research is also branching out from crop diagnosis into irrigation, UAV monitoring and sustainable farm automation. TinyML has been leveraged to monitor and interpret vegetation-index anomalies and environmental data to make water-management decisions at the local level [16]. Similarly, IoT-based TinyML approaches have been proposed for sustainable precision irrigation, which can assist in autonomous and energy-efficient agriculture management [21]. The TinyML frameworks shown here provide a means for processing aerial information on the farm using transfer learning, and for decreasing the computational requirements of UAV-enabled smart farming [23]. In summary, these research studies suggest that TinyML holds significant potential for enhancing the responsiveness, energy efficiency, affordability, and autonomy of smart farming. However, there are several restrictions on the diversity of datasets, environmental variations, hardware requirements, generalization of models, energy supplies, security, and field testing at a large scale. The challenges highlight the necessity of effective, versatile, and hardware-efficient TinyML solutions that can withstand a broad range of agricultural scenarios.

Table 1. Literature Survey of TinyML Applications in Smart Agriculture

Ref. No.	Methodology Used	Findings	Limitations
[1]	Comprehensive survey of TinyML architectures, algorithms, hardware, and deployment strategies	Identified on-device inference, model compression, and hardware optimization as major enablers of low-power AI	Broad survey; limited agriculture-specific experimental validation
[2]	Optimized TinyML models integrated with UAV-based monitoring and adaptive path planning	Demonstrated the potential for efficient aerial agricultural monitoring using edge intelligence	UAV deployment can be affected by battery capacity, environmental conditions, and computational constraints
[3]	Lightweight deep learning/TinyML models for apple and mango leaf disease detection	Showed that compact models can support crop disease recognition on resource-constrained devices	Limited crop and disease diversity may affect generalization
[4]	Attention-optimized TinyML models for agricultural sensor-data processing	Improved low-power processing and enabled intelligent analysis on edge microcontrollers	Limited hardware resources can constrain model complexity and scalability
[5]	Domain-adaptive TinyML for pest and disease detection	Addressed variations between training and deployment environments and improved adaptability	Domain shifts and limited local datasets remain challenging
[8]	IoT-based TinyML system for real-time rice leaf disease detection	Demonstrated real-time crop disease monitoring using embedded edge intelligence	Focused mainly on rice disease detection and may require broader field validation
[9]	Deployment-oriented review of low-cost, low-power edge AI and TinyML	Highlighted affordability, energy efficiency, and local processing as important for resource-constrained farming	Primarily a review; limited standardized experimental comparisons
[10]	Comparative evaluation of machine learning models for early pest infestation detection	Demonstrated the usefulness of ML for automated and early identification of crop pests	Conventional ML approaches may require improved edge optimization and larger datasets
[11]	TinyML-based plant disease detection for resource-constrained agricultural communities	Showed the feasibility of localized disease detection without relying heavily on cloud computing	Dataset and deployment conditions may be geographically limited
[12]	TinyML-based classification of bean crop diseases using compact models	Demonstrated the applicability of TinyML to crop-specific disease classification	Limited crop scope and constrained computational resources may affect scalability
[16]	TinyML-based NDVI anomaly detection and model	Supported efficient vegetation monitoring and localized irrigation decisions	NDVI-based analysis can be influenced by sensing conditions and environmental variability

	optimization for precision irrigation		
[19]	Knowledge distillation with TinyML-enabled IoT edge framework for weed classification	Enabled compact edge models while retaining knowledge from larger models	Distillation effectiveness depends on teacher-model quality and representative training data
[21]	TinyML and IoT integration for sustainable precision irrigation	Supported autonomous, energy-efficient irrigation management through edge intelligence	Real-world deployment requires robust sensors, connectivity, and long-term validation
[23]	Transfer learning and TinyML for UAV-assisted smart farming	Demonstrated efficient edge-based processing of UAV agricultural data	UAV energy limitations, environmental variation, and model-transfer challenges remain

Table 1 summarizes some of the representative studies on smart agriculture with TinyML, including disease and pest detection, UAV monitoring and support, weed classification, sensor processing, and precision irrigation. The research shows the progress towards low-power, real-time agricultural intelligence and the fact that there are still key issues regarding generalization, hardware limitations, data set diversity, and field deployment.

3. Methodology

3.1 Data Acquisition

The first step collects agricultural data from various sources to give the TinyML system a variety of inputs. Leaf and crop images can be collected through the use of smartphones, cameras, or field imaging devices, and UAVs and drones can collect aerial images for large area monitoring. The environmental sensors measure the temperature, humidity, light intensity and moisture content of the soil. Soil and irrigation data can also be used to aid water-management applications. Structured agricultural data publicly available may be included to expand the size and diversity of the data sets. The proposed framework can solve the problems of plant disease detection, pest identification, weed classification and precision irrigation in various field conditions by combining the image, sensor information and environmental data.

3.2 Data Preprocessing

The data is preprocessed to enhance the quality, consistency, and appropriateness for training the model. Images of agriculture are resized to a common resolution and pixel intensity variations are reduced by normalising the images. Where necessary, noise and irrelevant image regions are removed. To mitigate overfitting and enhance training diversity, data augmentation techniques, such as rotation, brightness adjustment, flipping, and scaling, are employed. Data from the sensors are scrubbed, normalized and validated for missing/outlier data. The processed samples are marked with crop type, disease class, pest category, weed type or disease severity. Lastly, the entire data set is split into training, validation and testing sets for model development and evaluation.

3.3 Model Development and TinyML Optimization

During this phase, light machine learning models are created for agricultural classification or prediction tasks. Depending on the target application, MobileNet, EfficientNet-Lite, compact CNNs, or other networks that are efficient in terms of resources can be chosen. First of all, the models will be trained on a high-performance computer, using the

prepared training set. Optimization methods such as pruning, quantization and knowledge distillation are used to shrink parameters, memory usage and computation complexity to make the models appropriate for constrained devices. In addition, transfer learning can be used to enhance performance in agricultural data sets that are small. Optimized models are tested with accuracy, precision, recall, F1 score, model size and computation requirement, and the best performance model is chosen.

3.4 Conversion for Edge Deployment

Selected model is converted to a format suitable to deploy on resource-constrained edge hardware. The trained model can be transformed into an inference format that is lightweight and fits well on microcontrollers, like TensorFlow Lite for Microcontrollers. In the conversion, optimization including the quantization is used so that the memory and calculation amount of the model can be reduced, and the model can predict well. The converted model is then evaluated to see its energy consumption, storage space requirements, inference latency, and RAM usage. Optimization is done hardware-specific, based on the characteristics of the chosen microcontroller/edge board. Model validation on the target hardware assures that the model can be run reliably before it is actually deployed in the field for agriculture.

3.5 Edge Deployment

The TinyML model is optimized and deployed directly to the edge device – typically an Arduino class microcontroller, an ESP32, STM32, etc. – embedded platform. The deployed model gets new observations of the data from agricultural sensors or imaging devices continuously. It does not send all raw data to a cloud server, rather inference is done locally on the device which will make rapid real-time predictions and reduce the communication needs. The system can diagnose plant diseases, pests, weeds, or abnormal crop conditions, based on the prediction. The edge device can send alerts or activate actuators like irrigation systems, sprayers, or warning systems. It also enhances the operation of the system in regions with low or unstable network connectivity.

3.6 Communication and Visualization

An edge device sends out the selected prediction results, alerts and pertinent sensor data to a remote platform if communication is needed. Depending on deployment conditions, lightweight communication technologies like MQTT, LoRa, Wi-Fi, Bluetooth, or cellular networks can be chosen. The system does not have to continuously stream the images or sensor streams but can provide information that has been processed in order to lower bandwidth and energy usage. History of observations can be stored in cloud or server infrastructure for further analysis. Disease classifications, irrigation conditions, environmental measurements and alerts can be displayed in a meaningful format on a dashboard or in a mobile application. It helps farmers or agricultural managers to keep track of the field's conditions from a distance and make informed decisions about management - at the right time.

3.7 Continuous Monitoring and Improvement

The last step is to set up a continuous feedback loop for enhancement of the reliability of the system following deployment. The agricultural environment is periodically monitored by obtaining new images, sensor measurements, environmental observations and prediction results. The data can be used to reveal false forecasts, unknown diseases, shifts in the environment or new traits in the crops. If enough new data is available, the model can be retrained or fine-tuned with the new data. The optimized model is then optimized once again and deployed to the edge devices. The performance is measured at all times through two metrics: classification accuracy and F1-score, inference latency, memory consumption, and energy consumption. This iterative approach enables the TinyML system to adjust to variations in the field and continue to provide accurate performance over time.

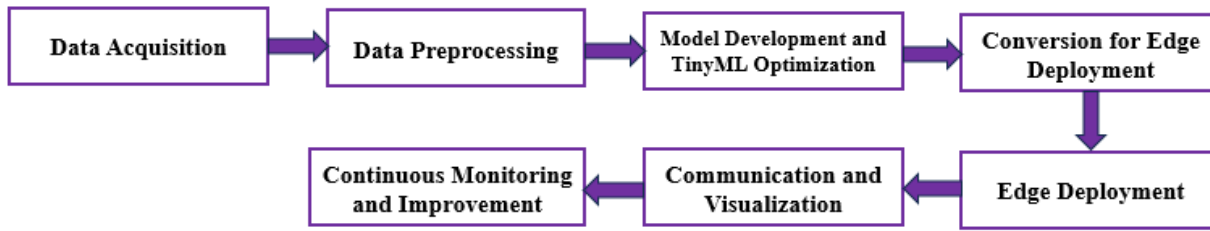


Fig. 2 Proposed TinyML-Based Edge Intelligence Framework for Smart Agriculture

Fig. 2. presents the proposed workflow for implementing a TinyML-based intelligent agricultural system. The process begins with data acquisition, where plant images or sensor data are collected from the field. The collected data are then subjected to data preprocessing to improve quality and prepare them for model development. A lightweight machine learning model is developed and optimized specifically for TinyML deployment. The optimized model is converted into an edge-compatible format and deployed on a resource-constrained edge device. The system then performs local inference, while communication and visualization enable the results to be transmitted and presented to users. Finally, continuous monitoring and improvement allow new data and feedback to be incorporated for updating and improving system performance.

Pseudocode: Proposed TinyML-Based Smart Agriculture Framework

Algorithm: TinyML-Based Smart Agriculture
Input:
Crop images, UAV images, sensor data, agricultural datasets
Output:
Real-time agricultural prediction and decision
1. Collect images and environmental/sensor data.
2. Clean, resize, normalize, and label the collected data.
3. Apply data augmentation to training samples.
4. Split data into training, validation, and testing sets.
5. Select a lightweight ML architecture.
6. Train the model using the training dataset.
7. Optimize the model using quantization, pruning, or knowledge distillation.
8. Evaluate accuracy, precision, recall, F1-score, memory usage, and inference latency.
9. Select the best-performing optimized model.
10. Convert the model into an edge-compatible format.
11. Deploy the model on a suitable microcontroller/edge device.
12. Collect real-time agricultural observations.
13. Perform local inference on the edge device.
14. Generate prediction, alert, or control action.
15. Transmit selected results to the dashboard/cloud.

16. Collect new field data periodically.
17. If performance decreases:
Retrain and optimize the model.
Redeploy the updated model.
18. Continue monitoring and improvement.
19. End.

4. Results

The results were derived from 15 representative works that focused on TinyML applications for smart agriculture, such as plant disease and pest detection, monitoring with UAVs, precise irrigation, weed classification, agricultural sensor processing and edge intelligence. The results of the reviewed studies were analyzed using a structured numerical literature approach. The studies were performed on different datasets, on different hardware platforms, with different model architectures, and different evaluation protocols and hence the results were not treated as direct experimental measurements. The majority of applications were focused on detecting plant diseases and pests (6 studies, 40.0%), followed by general TinyML and deployment-oriented research (3 studies, 20.0%), as shown in Table 2. Weed classification and agricultural sensor processing each had 1 (6.7%) study while UAV based agricultural monitoring and precision irrigation had 2 (13.3%) each.

Table 2. Distribution of TinyML Applications in Smart Agriculture

Application	No. of Studies	Share (%)	Edge/On-Device Focus (%)	Real-Time Focus (%)
Plant disease and pest detection	6	40.0	100	83.3
UAV-based agricultural monitoring	2	13.3	100	100
Precision irrigation	2	13.3	100	100
Weed classification	1	6.7	100	100
Agricultural sensor processing	1	6.7	100	100
General TinyML/deployment	3	20.0	100	66.7
Total	15	100.0	100	86.7

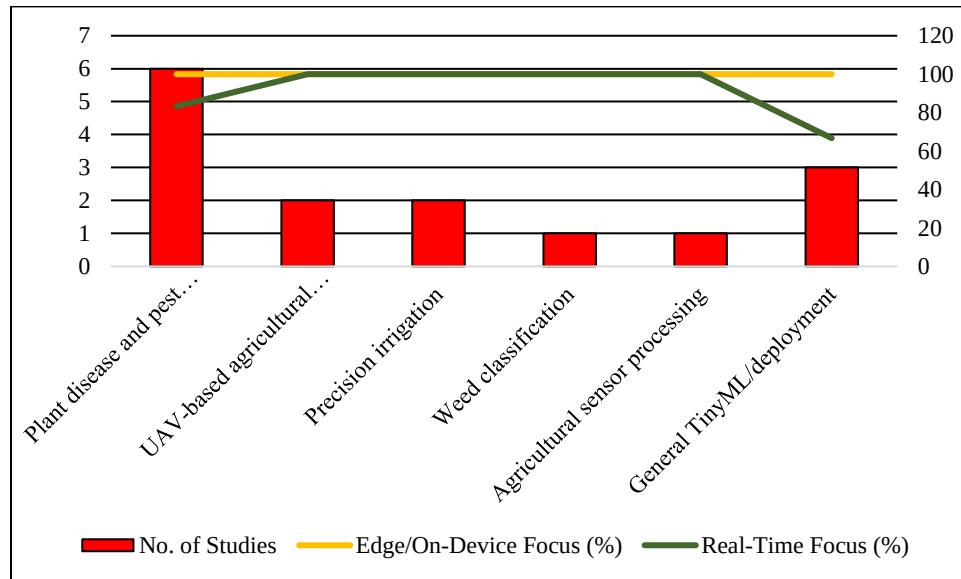


Fig. 3. Distribution of TinyML Studies by Application and Focus

In the figure above (Fig. 3), the distribution of the TinyML studies reviewed is shown after being rendered numerically, along with the focus of both the edge/on-device and real-time domains. The most studies (6) or 40.0% of literature selected is on the topic of plant disease and pest detection. The next largest areas of General TinyML/deployment research follow with 3 studies (20.0%) each for UAV-based agricultural monitoring or precision irrigation (13.3%). The contributions from weed classification and agricultural sensor processing are each a single study (6.7%). Similarly from the figure, all categories of applications have 100% real-time focus, while the on-device focus is 100% for all categories. The distribution shows that there is a lot of focus on monitoring crop health. To conclude, all studies that examined plant disease or pest detection (6 out of 15 studies, 40.0%) were suitable for local image classification and early diagnosis of plant diseases or pests, which were the applications considered in this study [3, 5, 8, 10, 11, 12]. In general, these studies focused on lightweight architectures and resource-conscious deployment, and thus, disease recognition is one of the most prevalent application fields of agricultural TinyML. UAV-assisted approaches (13.3%) were used to describe the use of edge intelligence for aerial agricultural monitoring and autonomous field assessment [2], [23]. The use of TinyML for localized water-management decisions based on vegetation and environmental information also showed increased use, with precision irrigation being 13.3% of the total.

In addition to the above, the analysis reveals that all 15 selected studies introduced an edge or on-device processing perspective, and 13 (86.7%) explicitly included a real-time or near-real-time perspective. This result confirms the key role of low latency inference in TinyML-driven farming systems. There are studies that have explored knowledge-distillation methods for decreasing the complexity of models for weed classification [19] and attention-based optimization for agricultural sensor processing on low-power microcontrollers [4]. General TinyML research accounted for 20.0% of the literature selected, focusing on model compression, deployment efficiency and overall edge device requirements [1], [9], [22]. Overall, the results suggest that existing research is progressing towards decentralized agricultural intelligence that would enable data processing in proximity to the sensors and hence reduce the reliance on the communication infrastructure and cloud computing. In terms of deployment, the studies reviewed highlight three key traits: low computing requirements, real-time processing and energy-efficient operation. Local image inference can be used for disease and pest detection, and continuous processing of environmental measurements can be used for irrigation and sensor-based applications. The TinyML approach can be extended to mobile edge platforms with the

emergence of UAV applications, adding new requirements for computational efficiency and energy management. Even with these developments, it is still concluded that comparisons in the numerical literature are still rather scarce. Many of the datasets, hardware, model architectures and evaluation metrics are different, making it difficult to draw clear comparisons from the accuracy, latency, memory usage and energy usage results. For future experimental research, it is proposed to use standard benchmark datasets, and report accuracy, precision, recall, F1-score, inference latency, model size and RAM usage, to facilitate a more consistent evaluation of TinyML-based agro-systems.

5. Discussion

The literature surveyed shows that TinyML is proving to be a viable way to implement intelligent agricultural applications on edge devices with limited resources. Previous research indicates that light-weight machine learning models are able to detect plant diseases, pests, weeds and crop conditions, and decrease the reliance on cloud infrastructure. TinyML's seamless integration with IoT sensors further allows for real-time and ongoing monitoring on-site and quick decision-making. This edge-based processing can lower communication latency, bandwidth usage and energy usage, and is well suited for rural and developing agriculture. Precision agriculture is another application where UAV-based TinyML systems can be beneficial, leveraging aerial imaging, adaptive path planning, and efficient edge inference. For deployment of compact models, knowledge distillation and transfer learning have further led to a substantial improvement of feasibility, without significantly compromising the classification performance. Research on irrigation water use efficiency and NDVI anomaly detection has demonstrated that TinyML has the potential to contribute to the optimization of resources by allowing for the detection of crop water stress and abnormal vegetative condition at appropriate time. But there are still difficulties in the areas of memory, computational power, dataset variety, model generalization, and variability in the environment. Therefore, the performance of the model across various crops, locations and field conditions is crucial and domain adaptation is an important part of this. In summary, the literature shows that TinyML is a viable platform for low-cost, energy-efficient, autonomous, and scalable smart agriculture systems.

6. Conclusion

TinyML is an emerging technology that will serve as a solid building block to create smart and sustainable farming systems that can run directly on devices with limited resources. These reviewed studies have shown its usefulness for plant disease and pest detection, weed classification, precision irrigation, UAV-based crop monitoring and IoT-based field management. TinyML processes data locally, which decreases the reliance on cloud connectivity, communication overhead, response time, and enables the use of energy-efficient agricultural decision-making. These qualities are particularly useful in the small scale farming and developing areas where consistent internet connection, computing facilities and monetary resources can be a constraint. Model compression, transfer learning, attention mechanisms and knowledge distillation enhance the compatibility of Machine Learning models to microcontrollers and similar low-power processors. While these benefits are substantial, there remain challenges, such as memory requirements, computational demands, model reliability, data heterogeneity, security considerations, and the need for model adaptation in varying environmental conditions, for practical implementation. Future research needs include multimodal TinyML, federated and privacy-preserving learning, adaptive models, explainable edge intelligence, and standardizing real-world agricultural benchmarks. The ability to integrate with UAVs, IoT sensors and autonomous farm equipment can further enhance system-level intelligence. In summary, TinyML has the potential to make considerable impact on precision agriculture by moving machine learning closer to the agriculture data sources, which supports affordable, autonomous, real-time and sustainable operations.

Conflict of Interest Statement:

The authors declare that there is no conflict of interest regarding the publication of this work.

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