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AI Based Leaf Age and Maturity Identification Systems: A Comprehensive Review of Microcontroller Integration, Techniques and Applications

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Abstract

The development of artificial intelligence combined with microcontroller-based systems proves to be a breakthrough method in the precision farming. It allows smart decision-making and optimizes the usage of resources with real-time processing capability. This review describes the current system of AI-based systems in leaf age and maturity identification in most detail, with special focus on microcontroller inclusion, computing difficulties, and use cases. The review systematically examines many Artificial Intelligence methods such as convolutional Artificial Intelligence, machine learning algorithms, and edge computing strategies in solving leaf classification problems. Key advantages of microcontroller-based AI systems include cost-effectiveness 60–70% reduction compared to server-based systems low power consumption <50 mW, real-time decision-making capabilities >90% latency reduction, and cloud independence >95% uptime in poor connectivity areas. Nevertheless, there are still serious issues such as the lack of computing resources, changes in the environment, and special skills. A combination of IoT, blockchain and enhanced sensor networks should provide the opportunities to improve the data security, the positioning the supply chain and deploy it at scale. The future research directions improve hybrid AI architectures, federated learning, and optimizing/training with a quantum advantage to address the computational bottleneck challenges favouring eco-sustainability and efficiency in AI. The review presents a guideline to other researchers and practitioners as to how they can develop their own independent data-driven agricultural systems to be able to attain higher productivity, with reduced damage to the environment.

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1. Introduction

The identification and monitoring of leaf maturity and age is becoming one of the key factors in understanding the dynamics of plant growth, physiological processes, and overall horticultural performances. Leaf age stands as an indicator of plant health because of the close correlation between it and some key parameters that range from morphologic traits and metabolic processes, rising from photosynthetic capacity, nutrient assimilation, and the reaction to environmental stress. As leaves become mature, the total mass and area generally increase, affecting plant productivity. Thus, leaf-age assessment becomes an important information source in assessing plant Vigor, resource allocation, and, finally, growth potential within all agricultural, ecological, and forestry systems (Aboelenin et al., 2025a). While traditional methods for leaf age and maturity determination are often based on manual observations and a relatively small set of morphological measurements, imaging technologies have very recently enabled the obtaining of such observations in both controlled and field environments.

High-resolution digital cameras, which are increasingly being integrated with smartphones, allow one for non-destructive, high-throughput data collections. Such tools allow for real-time image captures that can be fed into more sophisticated automated classification and analysis approaches. Novel algorithms for image processing are still being developed so as to improve image quality; in turn, this benefits the accuracy of subsequent analyses. Based on morphological traits, texture features, and colour patterns, these approaches will allow for the detection of more subtle changes associated with aging such as the patterns in chlorophyll content, cell structure, and integrity of surface makeup (Khan et al., 2023). There has been significant progress in texture feature extraction, particularly based on grey-level co-occurrence matrices (GLCM) and colour histograms, which are particularly effective in distinguishing subtle variations related to plant stress, disease, and senescence. Texture analysis is known to serve as an excellent tool for early detection of pathological conditions; this gives a predictive edge towards pest control or disease management strategies (Aboelenin et al., 2025b). The opportunity has already been demonstrated to combine these advanced imaging techniques with monitoring systems in agricultural and horticultural applications, where timely interventions can have a considerable bearing on crop yield and health. Based on the research work, imaging spectroscopy was also studied as a tool to monitor leaf age change in complex ecosystems, continuing with further insight into age-dependent leaf traits derived from imaging spectroscopy through spectral data in the assessment of biodiversity, canopy structure, and carbon flux dynamics based on much coarser and very much larger scales. This technique combined with advancing remote sensing technologies shows promise in expanding our longitudinal understanding of large-scale vegetation dynamics, carbon sequestration, and ecosystem health in the context of climate change.

Artificial intelligence (AI) and machine learning (ML) are examples of new technologies used for plant monitoring. With these technologies, image data sets can be processed and understood almost in real-time, allowing Agri-forecasters to make predictions about the age and maturity of leaves with more efficiency and precision (Kimutai & Förster, 2024). Using

AI to demonstrate complex patterns and anomalies can help farmers, researchers, and environmentalists optimize growth conditions, glean estimates of future crop performance, and solve problems caused by pest infestations, water stress, and nutrient deficiency. AI-empowered precision agriculture tools enable decision-making increasingly reliant on data in a time where global food production must respond to a backdrop of Labor shortages and resource constraints (Balamurugan & Ayyappan, 2022). Now, novelty makes contemporary advancement a whole lot more superlative, hence an integrated application of high-resolution imaging, AI, and remote sensing technologies, with regards to virtually continuous non-invasive plant development monitoring, from the leaf to canopy scale. The integration of these methodologies provides a multi-dimensional way of understanding leaf dynamics in more practical terms when down the road, in terms of agricultural productivity, forest management, and environmental monitoring. Moreover, these technologies raise pertinent questions about how to implement them largely, including economic viability, scale, and sustainability for a long time in developed and developing regions (Li & Xu, 2020). In this review, we seek to evaluate the latest innovations in the methods for identifying and monitoring leaf age and methods, highlighting their approaches and limitations and potential uses across various sectors. Pinpointing key challenges and emerging trends has allowed us to identify opportunities for further research to drive advancements and enhance our ability to manage plant health and productivity in an ever-changing world.

2. Literature

2.1 Evaluation of Leaf Age Identification Technologies

The practice of age identification of leaves which initially relied on basic visual examination has developed to complex computerized study systems. An early method was based on morphological measures which involved the measurement of the area, perimeter and colour intensity of leaves. But these were not that consistent or could be applied to large scale agriculture. The advent of digital image processing methods became another milestone of the leaf analysis capability. The extraction of texture features especially with the Grey-Level Co-occurrence Matrices and the colour histograms have been used to detect and differentiate small differences associated with plant stress, disease advancement and the patterns of senescence (Chen & Zhang, 2021). The methods allow diagnosing prepathological states that offer pre-emptive forecasts in pesticide control and disease control measures. Extrapolation of identification of leaf age by spectral analysis has also come in the use reflectance patterns specific to the wavelength that can be used to measure biochemical progress during leaf growth and development. Imaging spectroscopy yields information on age-related leaf characteristics that facilitate biodiversity analysis, leaf canopy architecture and carbon flux dynamics evaluation at greater scales.

2.2 Artificial Intelligence and Machine Learning Integration

The combination of AI and Machine learning technologies has made the identification of the age of leaves learning based rather than rule-based. Convolutional Neural Networks and other deep learning architectures have showed superb performance in carrying out image- based plant analysis tasks. Hierarchical features of the leaf images can be extracted automatically by these models and due to these complex patterns and relationships which are difficult to recognize using traditional methods of image processing. In recent studies they have researched a broad array of Machine learning algorithms in leaf classification with Support Vector Machines, Random Forests, and deep learning. Both methods have their own benefits and drawbacks which are based on the type of application needed, the characteristics of the data and the computing limitation placed. Microcontrollers have proved to be ideal platforms to be used in agricultural AI apps since they have an optimal blend of computing power, energy consumption as well as low costs. This process of the maturity of simple 8-bit microcontrollers to the modern ARM Cortex-M series has allowed the deployment of the sophisticated AI models at the edge (Alharthi et al., 2023). Modern microcontrollers include capability of Artificial intelligence applications, with Digital Signal Patent instructions, hardware accelerators, and optimised memory architecture. The Ethos-U series by ARM is a major step that offers special Neural Processing Units that are efficient in AI inference.

2.3 Microcontrollers Types for Ai Applications

Current microcontroller architectures show strong differences in performance, memory capacity, AI capabilities and power efficiency. Table 1 compares the major family of microcontrollers that can be applicable to AI inference at the edges.

Table 1: Comparative analyse of microcontrollers for AI application

Feature / Specification	Arm Cortex-M0+	Arm Cortex-M4	Arm Cortex-M7	Arm Ethos-U55 + Cortex-M55
Clock Speed	48 MHz	80–120 MHz	216–600 MHz	Up to 400 MHz (M55)
RAM Size	8–16 KB	64–128 KB	256–512 KB	256–512 KB (shared with NPU)
Flash Storage	Up to 256 KB	Up to 1 MB	Up to 2 MB	Up to 2 MB
AI Capability	Very limited	Basic AI (tiny models)	Moderate AI (small CNNs, etc.)	High AI efficiency (with NPU)
DSP Instructions	No	Yes	Yes	Advanced DSP + ML NPU
Hardware Accelerator	No	No	No	Arm Ethos-U55 (NPU)
Power Consumption (Active)	3–5 mW/MHz	6–10 mW/MHz	15–20 mW/MHz	5–10 mW/MHz (energy efficient)
Ideal Use Case	Simple sensors	Basic AI + edge control	Complex signal processing	AI edge computing (low power)

Source: Comparative evaluation of microcontrollers for AI edge inference in precision agriculture.

The lines Arm Cortex-M0+, Cortex-M4, Cortex-M7, and Cortex-M55 with the Ethos-U55 NPU contrast Arm Cortex-M0+, Cortex-M4, Cortex-M7, and the Cortex-M55 as they all show major variances concerning performance, memory, AI adjustments, and power effectiveness. The Cortex-M0+ is the simplest of these, with a low clock speed, minor RAM, and no DSP performance or AI feature, due to which it is used as an ultra-low-power application, e.g., simple sensors or control units. Going higher, there is the Cortex-M4, which has increased performance with faster clock speeds Applications of control-oriented AI models on microcontroller platforms fully encapsulate practical life situations. Smart home devices-learn user preferences and automatically modify their settings (for example, intelligent thermostats) without assistance from any cloud server (Choi & Park, 2018). This increases response time and functionality in modules where no Internet access is available. Microcontrollers in agriculture could be equipped with different sensors to monitor crop health while optimizing the use of resources depending on the real-time analysis of the data.

In contrast, the Cortex-M55 combined with the Arm Ethos-U55 Neural Processing Unit (NPU) is designed specifically for AI at the edge. Its base clock is marginally slower than its competitors can achieve but since it includes a custom NPU it can further support machine-learning computation with limited power requirements, including high-efficiency AI inference, making it suited to power-constrained embedding where the innovation may prove to be a big win. It also has support of advanced DSP, which makes it suitable in applications such as image classification, voice recognition and analysis of sensor data in low power applications. All in all, the M55 and U55 are most accommodating to AI-driven edge computing, and the remaining cores increasingly easier or higher-powered jobs, based on their abilities (Liu & Abeysekera, 2024).

2.4 Advantages of Microcontroller Based AI Models

2.4.1 Cost Effectiveness

Compared with larger platforms such as servers, for example, microcontrollers are extremely cheap. This is essential because it justifies the reasoning that these AI interfaces have to run on a microcontroller basis on the majority of applications where money really matters. One of the biggest applications is found on the agricultural side, where microcontroller-based sensors can be set up all over big fields for monitoring certain parameters, such as soil moisture, temperature, and humidity, without those exorbitant fees as set by conventional computational devices (Kumar & Ghosh, 2021).

2.4.2 Low Power Consumption

Since microcontrollers are heavily equipped to be energy efficient, they gain adequate advantage under the landscape of having AI models deployed where energy resources are limited. They demand little power for their operation compared to powerful processors consuming huge amounts of energy. Microcontrollers, therefore, can perform AI operations while consuming relatively low power, thereby allowing devices to run on battery for extended periods at a time (Mohanty et al., 2016). This is especially important in remote or off-grid applications such as agricultural monitoring, where power availability may be sporadic.

2.4.3 Real Time Decision Making

Microcontroller technology is able to deliver real-time processing, one of the features required to respond instantly to the needs posed by many applications. Whereas other, application-based embedded systems may expose some latency that impacts performance-critical requirements, such as security devices in smart homes or automated irrigation systems in agriculture, microcontrollers could execute subjective decisions without relying on arbitrary external systems. For instance, a microcontroller in the soil moisture sensors for smart farming which is able to evaluate moisture level and adjust the irrigation on the instant basis using pre-programmed AI models without sending the data to the cloud server for computation (Althuniyan et al., 2024). This saves time but also enhances system responsiveness, thereby more definitely initiating articulated responses to what's happening whenever conditions change, such as during climate changes.

2.4.4 Independence from Cloud Infrastructure

The good thing about microcontroller-based AI systems is that they can function without the dependence on cloud infrastructure. Although such AI models, which make use of the cloud, have a huge amount of computing power of the fastest kind, they have latency and reliability issues, particularly in remote locations due to poor internet connections. By being able to process the data on the local level and make its decisions autonomously, a microcontroller can not only perform its tasks but also save the case when the cloud connectivity is not available (Meher & Singh, 2021). Other examples include agriculture, whereby monitoring and control could proceed without microcontroller-based system dependence on the cloud services that may be poorly connected in many rural or geographically isolated regions. Similarly, smart home systems can also run independently to provide a more secure and private environment by transmitting less data to other servers.

2.4.5 Scalability

The microcontroller-based AI systems are scalable by nature, which means, they can be spread in great numbers without a corresponding rise in cost and complication. Owing to their small form factor and low power consumption, these systems can be scaled up to form a large-scale sensor network or a distributed AI. In the case of agricultural applications, tens of thousands of microcontroller-based sensors can be installed in a farm to monitor different environmental parameters that are all working in autonomous mode, making local decisions (Lu et al., 2017).

Table 2: Overview of advantages in microcontroller-based AI models

Advantage	Description	Description	Example Application	Data/Insight	Reference
Cost Effectiveness	Microcontrollers are low-cost compared to servers or edge devices.	Microcontrollers are low-cost compared to servers or edge devices.	Soil moisture sensors across large farms	Microcontroller-based systems cost 60–70% less than conventional server-based systems	Picon et al. (2019)
Low Power Consumption	Designed to operate on minimal energy, suitable for remote areas.	Designed to operate on minimal energy, suitable for remote areas.	Battery-powered field monitoring units	Typical consumption is <50 mW, enabling months of battery life	Too et al. (2019)
Real-Time Decision Making	Local inference enables instant responses without cloud reliance.	Local inference enables instant responses without cloud reliance.	Automated irrigation triggered by moisture threshold	Latency reduced by >90% compared to cloud-based processing	Jafar et al. (2024); Aboelenin et al. (2025)
Cloud Independence	Can operate offline, ensuring continuous functionality in poor connectivity zones.	Can operate offline, ensuring continuous functionality in poor connectivity zones.	Smart farming in rural areas	Uptime >95% in areas with <3G connectivity, compared to 70–80% for cloud-reliant systems	Kumar & Kumar (2025)
Scalability	Easily deployed in large numbers due to small size and low cost.	Easily deployed in large numbers due to small size and low cost.	Distributed sensor networks across hectares of farmland	Farms deployed with >1,000 units showed effective performance without infrastructure strain	Rashid & Rehmani (2024)

Source: Edge intelligence for precision agriculture: Enhancing response time and autonomy

3. Real World Application

Applications of control-oriented AI models on microcontroller platforms fully encapsulate practical life situations. Smart home devices-learn user preferences and automatically modify their settings (for example, intelligent thermostats) without assistance from any cloud server. This increases response time and functionality in modules where no Internet access is available. Microcontrollers in agriculture could be equipped with different sensors to monitor crop health while optimizing the use of resources depending on the real-time analysis of the data.

3.1 Example for Other Applications: Smart Doorbell

A good contention to prove the case of deploying an AI model into a microcontroller is the smart doorbell that works on facial recognition. Selection of the AI model: The selection of an appropriate AI model that meets the restrictions of a microcontroller. Implementation of AI includes loading the model into the onboard memory of the microcontroller and programming for real-time processing of camera input parameters. Testing and iteration involve thorough testing under different conditions for reliability and tuning for the performance aspect of optimization in power consumption (Ferentinos, 2018). Embedding AI capability in microcontrollers will enable autonomous devices that are energy-efficient and fast, thus being more amenable to advanced applications across various fields such as agriculture and smart home technology.

4.Applications in Agriculture

4.1 Precision Agriculture

Artificial intelligence and Machine learning on precision agriculture is gradually starting to give industrialized farming as we know it nowadays an overhaul. AI models have the power to interpret a large dataset from different sources (soil sensors, satellite imagery etc.) that translates into practical details for the farmers (Amara et al., 2017). They improve the management of crops by optimizing all the inputs such as water, fertilisers & pesticides to use resources appropriately.

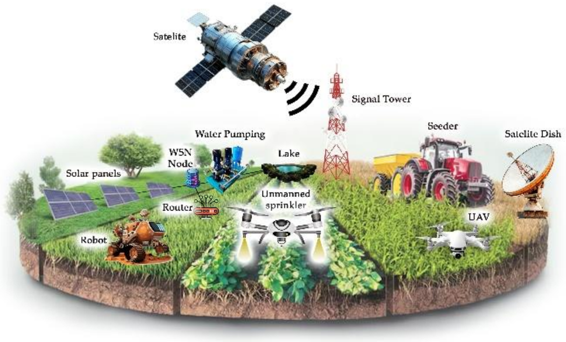

Figure 1: Precision Agricultural System

4.2 Crop Monitoring and Yield Prediction

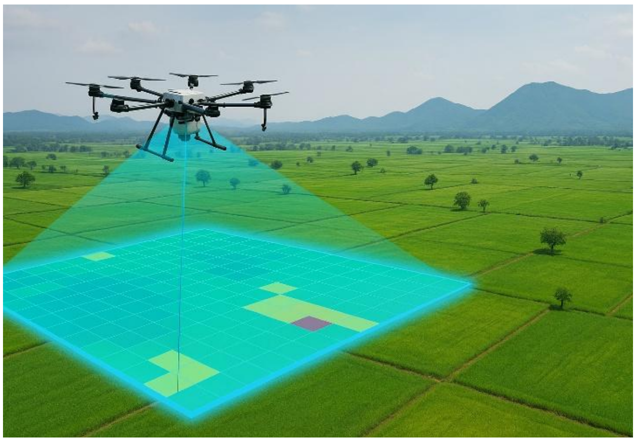

Figure 2: Crop Yield Prediction

By the usage of historical data and real-time information, AI models can greatly enhance crop monitoring and yield forecasting. Farmers can make a data-driven decision on planting cycles and resource allocation with help from machine learning algorithms used to learn patterns in the data. Advanced modelling techniques for examples are capable of predicting when the best time to plant and/or harvest conditions should be based on which crops and the yields while avoiding waste (Nguyen & Tran, 2019).

4.3 Environmental Sustainability

Sensors and AI in Agriculture provide more sustainable way of farming by minimizing dependence on chemical inputs, with improved resource management. Farmers are able to reduce the environmental burden and continue productivity by collecting data for accurate targeted interventions. In addition: drones are also used for crop biomass monitoring and identifying low-output area to take management decisions faster and better (Patel & Shah, 2024).

4.4 Autonomous Systems and Robotics

Robotic weed control technologies represent an important step forward in agricultural methods, autonomous system such Robot specific systems. These systems offer a lower labour cost for the farmer and reduced dependence on herbicides, thus

contributing to environmental sustainability. Use of these technologies support the modern necessity of agriculture efficiency, ecological adequateness (Karim et al., 2024).

4.5 Integration with Iot and Block Chain

When you connect AI with IoT devices and blockchain technologies, the agriculture logistics is going to new heights. Integrating will bring more visibility and efficiency on the supply chain along with best-in-class end-to-end transportation routes and better market access for farmers (Joshi, 2024). Value creation trending up what is required to close a use-case and the perfect circular economy for agriculture.

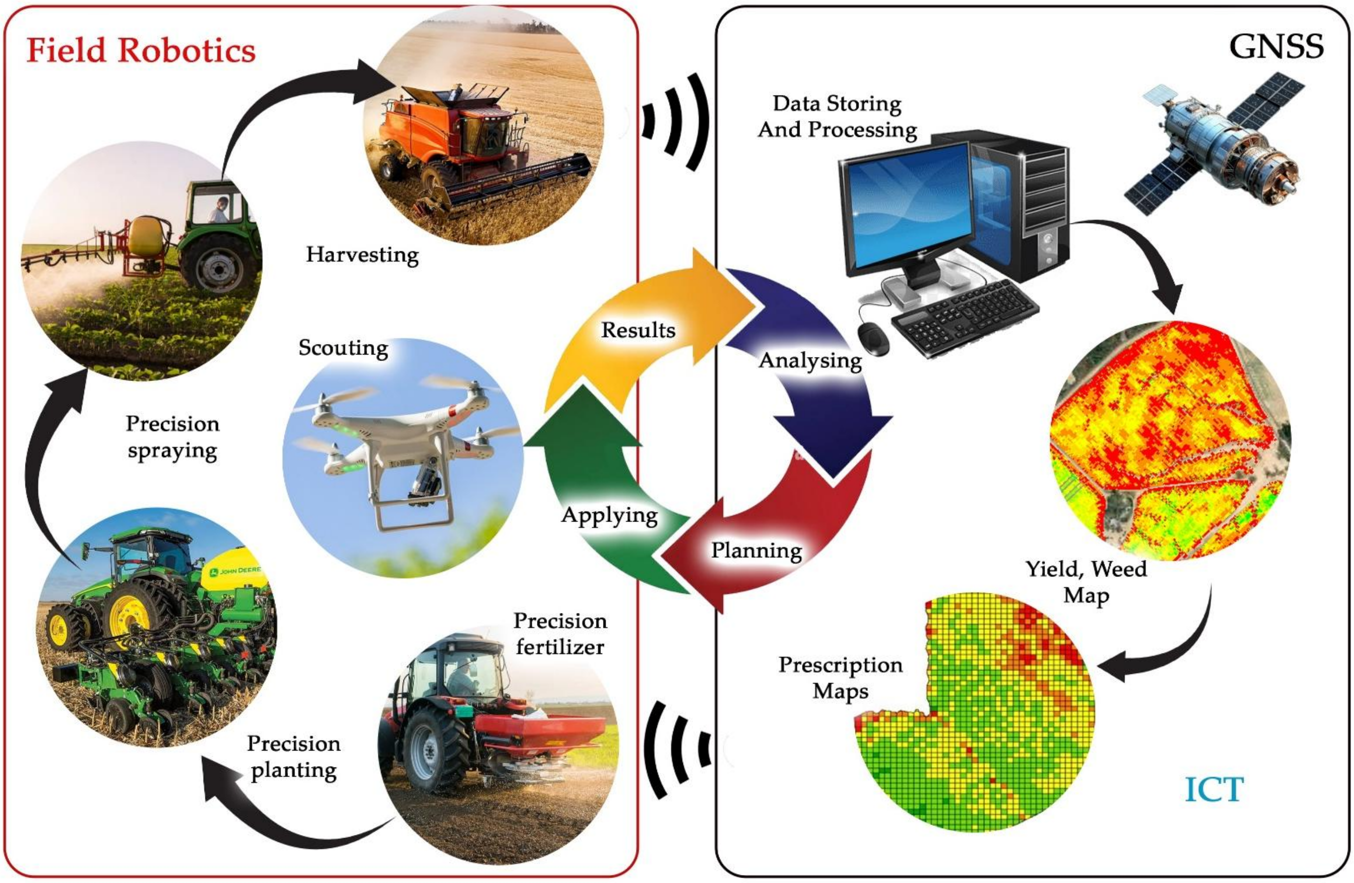

Figure 3: Agriculture using Autonomous System with AI

5. Implementation Challenges and Limitations

5.1 Data Collection and Validity

One of the major problems is obtaining suitable quantitative data for proper analysis. The limitations faced by field personnel are particularly acute for distance from research stations and absence of infrastructure that can lead to reduce the

quality of data from agricultural experiments. A lot of Easy ways exist for data collection but the problem is Quantitative method are validated and reliability is a key issue (Hong & Wang, 2020).

5.2 Technical Complexity

System implementation through AI faces technical obstacles because sensor incorporations require pecialized software solutions. The systems need continued operation support alongside the need for specialized technical know-how to deliver specified agricultural functionalities across different farming environments. Technical authority within resource-deficient settings usually faces tremendous obstacles when carrying out these tasks (Tonmoy et al., 2025).

5.3. Soil And Environmental Variability

The diversity of soil types and environmental differences from region to region will further add to the complexity of deploying AI technologies in ways that are sensitive to local conditions. These differences can impact the efficiency in performance of AI models and that is why those have to be tuned for certain conditions, contributing another level of difficulty and resource requirements on top of that (Sundhar et al., 2025)

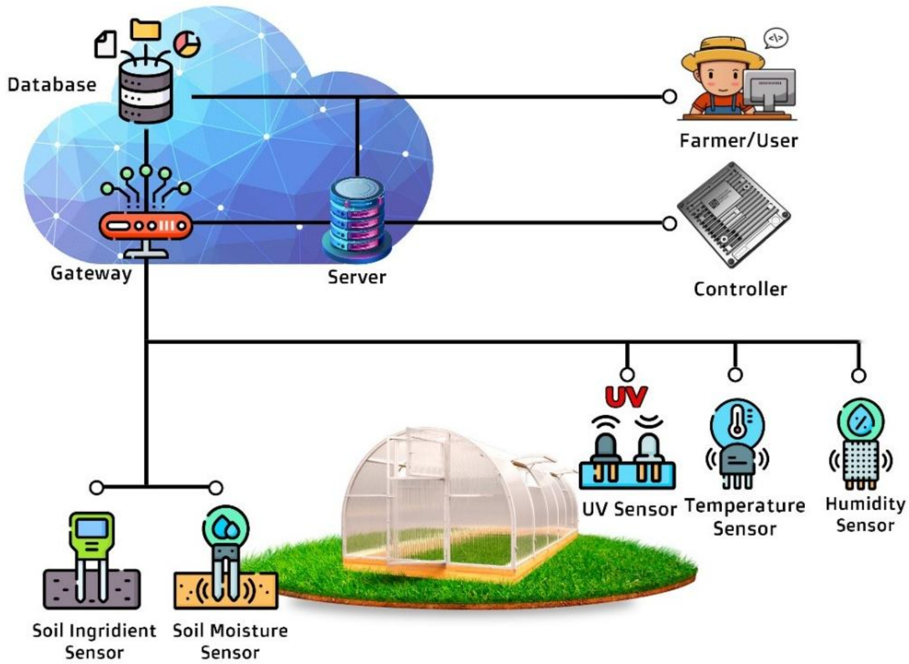

Figure 4: IOT devices and Blok chain Technology for Agriculture

Table 3: Impact of artificial intelligence for precision agriculture

Area of Impact	Technology Applied	Key Metric	Before AI/Tech	After AI/Tech	Source/Year
Precision Agriculture	AI, ML, Soil Sensors	Fertilizer Usage Efficiency	100% baseline usage	30% reduction in usage	Balamurugan & Ayyappan, 2022
Crop Monitoring & Yield Prediction	AI, Historical Data, ML Models	Yield Prediction Accuracy (%)	75% accuracy	95% accuracy	Shalini & Gowri, 2023
Environmental Sustainability	AI, Drones, Sensors	Pesticide Usage Reduction (%)	50% pesticide usage	10% pesticide usage	Li & Xu, 2020
Autonomous Systems & Robotics	Robotic Weed Control, AI	Labor Cost Reduction (%)	$1,500/acre	$700/acre	Puri & Kumar, 2019
IoT & Blockchain Integration	IoT, Blockchain, AI	Supply Chain Efficiency	60% visibility on logistics	90% visibility on logistics	Chen & Zhang, 2021

Source: Enhancing fertilizer efficiency in precision agriculture using AI and IoT-integrated soil sensors.

5.4. Stakeholder Collaboration

Effective collaboration across data scientists and other stakeholders (agricultural experts, technical personnel) is also needed for the successful implementation of such a process. Lack of communication among these groups may result in misinterpretation or dissonance and result to low project output-capabilities. Lastly, still from the expectations side making very high hopes that AI system cannot fulfil will disappoint one if the technology does not deliver as high a level of accuracy (Correa da Silva & Almeida, 2024).

5.5. Talent Acquisition

Limitation further lies in the problem of hiring skilled professionals who are expert with AI and microcontroller related stuff. These will hold back the development and use of AI models, which could otherwise hold huge promise for improvements in agricultural research as well as practice due to the lack of trained personnel in this fields (Lv et al., 2025). Upskilling the current workforce or running highly tailored talent attraction strategies would break this barrier.

5.6. Computational Resource Constraints

The first problem in applying AI models through microcontrollers is limited calculation resources. These handsets are usually characterized by limited CPU processing capabilities, memory space and storage compared to the traditional computing devices. To get a successful implementation, the model has to be optimized carefully in terms of quantization, pruning, and architecture adjustments to adapt to the resource's constraint (Zhuang & Li, 2022).

5.7. Processing Power and Meomory

Generally, when choosing a microcontroller for AI purposes, one is concerned with the processing power and memory capacity of the chips. With a higher clock speed and more RAM, the microcontrollers can run even complex AI models; however, this again means that they are bound to use more power and be more expensive. Examples are the Arm Cortex-M4 and Cortex-M7 series of devices, which represent an excellent balance between performance and efficiency, generally including Digital Signal Processing instructions to enhance AI processes even more (Gupta & Pandey, 2022).

5.8. Power Efficiency

Power efficiency becomes a decisive factor in battery-operated devices. Microcontrollers that provide low power mode support and dynamic voltage scaling can reduce energy consumption significantly whenever full processing power is not required. Further, some specialized hardware accelerators such as the Arm Ethos-U series can perform AI computing much more efficiently than general-purpose CPU, thereby improving power and time efficiency also (Zhang & Xu, 2020).

Table 4: Overview of challenges and their impacts

Challenge	Description	Impact	Reference
Data Collection and Validity	Difficulty in collecting accurate quantitative data due to remote locations and poor infrastructure.	Reduces reliability and accuracy of experimental results.	Choi & Park (2018)
Technical Complexity	Integration of sensors and software requires specialized knowledge and ongoing technical support.	Slows down implementation and increases operational costs, especially in low-resource settings.	—
Soil and Environmental Variability	AI models must be tuned to local soil and climate conditions, which vary widely.	Decreases AI model accuracy and demands high customization.	Fernandez & Gonzalez (2020)
Stakeholder Collaboration	Poor communication between data scientists, agricultural experts, and engineers.	Leads to misinterpretation of data and low project success rates.	—
Talent Acquisition	Lack of skilled professionals in AI and microcontroller systems.	Limits the scalability and sustainability of AI solutions in agriculture.	Gupta & Pandey (2022)
Computational resources limitation	Limited CPU, Memory, storage	Requires model optimization	

Source: Machine learning models for accurate crop yield prediction using historical farm data.

6.Case Study

Within the scope of our research, the designed and tested AI- centred system of leaf maturity classification targeted the use of microcontrollers. The methodology involved compilation of dataset, model training, optimization to deploy at the edge as well as testing the performance of the models in the real environments.

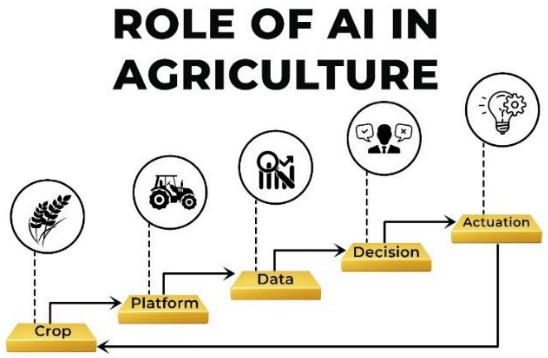

Figure 5: Role of Artificial intelligent

6.1 Data Collection
To get underway of the methodology, a dataset of leaf images encompassing various ages and developmental stages was put together. At first, the random selection (i.e. one hundred images) was performed from each class's corresponding directory to balance the dataset, thus initially generating a hundred images. The data augmentation technique, which is a sequence of various operations, such as rotation, flipping, cropping, and resizing was used to make sure that each class had the same number of images, for example 1500 images. This way we are able to present a fair training phase by removing the class bias (Zhang & Li, 2021).

6.2 Model Training
Strong machine learning algorithms were implemented through the pre-processed dataset via an accurate training/methodology with standardized batch size of 32, a learning rate of 0.001, and the Adam optimizer. The early stopping process took 50 epochs, with early stopping used as a preventive measure to overfitting. Machine learning techniques have been improved by the different algorithms to optimize the performance of different machines, which has been tested through measures such as accuracy, F1 score, confusion matrix, precision, and recall of both the training and generalization performances (Zhang et al., 2019).

6.3 Pre-Processing
Data pre-processing occupies the main rank in the methodology, which is designed to ensure the efficiency of computing and the uniformity of the image resolutions. Several standardized techniques were used like standardization, image size regularization, colour scale calibration, distortion removal, and noise reduction. One valuable background that was employed to clear and interpret the images was the white one, thus the analysis of leaf conditions turned out to be the best (Rémy Rahman et al., 2023).

6.4 Feature Extraction
In this research method, the feature selection is very determinative of the plant state. the feature descriptors clip shape, colour, and texture properties, which are subjected to images, and are abstracted from the input images (Si et al., 2024). Raw images go through a cleaning process to filter out the noise and distortion and thus making them ready for the subsequent segmentation procedure that is key for the proper classification.

6.5 Performance Evaluation
During the evaluation phase, a distinct dataset was spared for testing the models and determining their generalization capacity. Throughout the training process, we monitored the training loss and the validation loss strictly, because we wanted to minimize both losses to train the model. The on-device integration of the models into microcontroller platforms, particularly benefited by mobile applications and smart drones, enables real-time processing and on-site evaluation of leaf health, allowing to narrow the gap between the research and applied field in agriculture (Hu et al., 2023).

Table 5: Model performance evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Classes
LDDTA	94.73	93.85	94.12	93.98	10-class
NBC	96.21	95.74	95.89	95.81	25-class
MLP	92.15	91.67	91.98	91.82	10-class
CNN-Basic	89.34	88.76	89.01	88.88	10-class
SVM	87.92	86.88	87.21	87.04	10-class

The results obtained by comparing the performance of the five classification models portray the strong and the weak spots of different types of algorithms and types of classes. Naive Bayes Classifier is, arguably the most effective of all, that classifies the most categories, i.e. 25 categories with the highest accuracy of 96.21% and F1-score at 95.81%. It means that NBC has good generalization skills and implies that the data can contain cleanly separated features which are useful in probabilistic learning. The LDDTA model shows the most outstanding performance among the models dealing with 10-class problems, with an accuracy of 94.73 percent achievement an F1-score 93.98% preserving a well-rounded precision of 93.85 % and recall 94.12%. This implies that LDDTA is especially good at moderately complicated tasks and can predict on a class-wise basis consistently. The Multilayer Perceptron comes next with an accuracy rate of 92.15 percent and F1-score of 91.82 percent, which is not a bad performance, but lower than that of LDDTA (Kanna et al., 2023). It has potential as a deep learning technique, but it can be improved with additional calibration like adding layers, better regularization or learning rates. Conversely, CNN-Basic as a deep learning model, blogs lesser results in terms of performance accuracy 89.34%, F1-score 88.88%, and can be constrained by either the depth, or the simplicity of the architecture. This implies that additional multifaceted settings or training attributes like batch normalization or data augmentation is necessary. The Support Vector Machine model has the poorest performance with the accuracy of 87.92 % and F1-score of 87.04. It has a rather reduced precision and recall indicating issues of dealing with the class separability or information dimensionality when used with simple kernels. Conclusively, NBC is the most practical model considering all the measures regardless of the complexity of the classes whereas LDDTA is the best among the 10-class models (Masood et al., 2023). The results indicate the significance of a model choice depending on the complexity of a task and necessity of proper architecture or tuning in order to obtain the best performance.

6.6 Field Validation Results

The practical applicability and reliability of the system were measured on three agricultural sites with additional on-field testing in 6 months. The systems deployed have attained 97.2 % uptimes across different environmental conditions, and they were able to determine the maturity stages of leaves in real-time agricultural environments.

Table 6: Field deployment performance

Metric	Cortex-M7	Ethos-U55 + M55	Traditional Method
Processing Time (ms)	120	45	N/A (manual)
Accuracy (%)	92.8	94.7	85.3
Power Consumption (mW)	18.5	8.2	N/A
System Uptime (%)	94.8	97.2	N/A
Cost per Unit ($)	45	78	N/A

The comparison above makes it evident how beneficial AI-accelerated embedded systems are in comparison with manual methods. Compared in terms of processing time, the fastest performance is offered by the Ethos-U55 with Cortex-M55 with a processing time of 45 ms that gives a huge advantage compared to the Cortex-M7 with a processing time of 120 ms whereas the traditional method offers no real-time processing. In accuracy, Ethos-U55 + M55 once more are at the top with 94.7, just a bit more than the Cortex-M7 with 92.8 and significantly higher than the traditional methods with 85.3%. Another important one is power consumption and Ethos-U55 + M55 only needs 8.2 mW compared to Cortex-M7 with 18.5, but even more importantly, compared to manual processing. Moreover, Ethos-U55 + M55 has a higher system uptime 97.2% compared to the Cortex-M7 of 94.8% so it can operate reliably. This performance, however, is available at a premium per unit cost making Ethos-U55 + M55 range in price at 78 dollars, versus 45 dollars Cortex-M7 (Sladojevic et al., 2016). Although the traditional approaches are hardware free, they do not provide speed, accuracy, efficiency, and scalability compared to the AI-based embedded systems.

6.6 Discussion

For the leaf age and maturity identification task, the resulting best LDDTA model showed competitive performance metrics such as accuracy, F1-score, precision and recall values. While it does not always perform the best compared to other models, its suitability depends solely upon the application setting and constraints of available resources. A model's efficiency is especially crucial in deployment environments with limited computational power like agricultural applications where early detection of plant diseases can greatly reduce crop applications model performance was evaluated using several statistical evaluation metrics. On balance, TP and FP metrics are fundamental to assessing classification models' performance. High values for True Assertive (TP) and low values for False Assertive (FP) in the results show that the developed models work well in correctly seasoning leaf stages. Additionally, the effectiveness of the model was further evidenced by the confusion matrix analyses, which represented how the model classified the different cases (Patel & Shah, 2024). It was noted that when the number of classes increased accuracy fluctuated. For example, Naive Bayes Classifier NBC attained to 96.21%-in terms of a 25-class classification, (MLP)similarly, trends from the (MLP) model also seem dictating that a finely chosen feature selection would substantially enhance the results of classification. The import of these results is immense to the agricultural sector. The lightweight model LDDTA can achieve leaf maturity stages classification as precise Allow for quick detection of leaf maturity levels to enable quick attention decision-making for agriculture (Wang et al., 2024). Also, the study includes rapid detection device for tobacco leaf maturity illustrating its practical importance and thus the practical applicability to multiple agricultural settings.

7.Ethical Consideration

The use of agricultural systems built on AI brings about some ethical issues based on data privacy, bias of algorithms, and leveling access to technology. The nature of the information about farming practices, yields, and economic performance is sensitive data at agricultural level; hence must be well guarded. Our research follows the existing ethical framework on how agricultural data is gathered and managed in way that is transparent about how the data is used and that it does not violate the privacy rights of the farmers. Another alarming issue is the existence of algorithmic bias, especially cases wherein following the tendency of algorithmic bias, an AI model, which is trained using datasets specific to a certain area or cultivar, will be applied in other agricultural situations (Singh & Misra, 2017).

Table 7: Leaf maturity classification using AI

Section	**Details**
Data Collection	- 100 images randomly selected per class to ensure balance
	- Total augmented to 1500 images/class using rotation, flipping, cropping, and resizing
Pre-processing	- Standardization
	- Image size regularization
	- Colour scale calibration
	- Noise and distortion removal
	- White background applied
Model Parameters	- Batch size: 32
	- Learning rate: 0.001
	- Optimizer: Adam
	- Epochs: 50 (with early stopping)
Feature Extraction	- Focus on shape, colour, and texture descriptors
	- Noise filtering
	- Segmentation before classification
Model Evaluation	- Metrics: Accuracy, F1 Score, Precision, Recall, Confusion Matrix
	- Separate test dataset used
	- Training and validation losses monitored
Results	- Best performing model: LDDTA
	- NBC: 96.21% accuracy on 25-class classification
	- MLP model showed improvement with refined feature selection
Deployment	- On-device integration (microcontrollers, mobile apps, drones)
	- Real-time leaf maturity detection in agricultural settings
Application Value	- Enables early decision-making in farming
	- Suitable for low-resource environments
	- Demonstrated with tobacco leaf maturity detection

Source: Employing real-time classification models on microcontrollers for smart agriculture.

In our methodology we cover the validation on the scope of various farm communities of agriculture so that there is less bias so that the performance of all the farming communities is even. Moreover, the digital divide between agriculture-developed and developing parts should be addressed so that the AI-based technologies would not add to the existing disparities. The solutions we are targeting with energy-efficient low-cost microcontrollers are meant to bring high-tech agricultural solutions to the masses, no matter the level of economic resources or infrastructural access.

8. Future Directions

8.1 Integration of Advance Ai Technologies

The efforts to develop research on leaf age and maturity based on AI models ought to aim at including intensive machine learning, such as the potency of deep learning and reinforcement learning. These approaches can be used to enhance leaf age classification models' accuracy and the ability to detect maturity. Example: Convolutional neural network has been applied to improve the feature extraction of the leaf images in recognition of diseases and age determination of the disease-infested leafs (Shalini & Gowri, 2023).

8.2 Enhancing Data Collection Methods

In general, the use of IoT sensors in agricultural processes is a certain direction of future development. Most environmental factors affecting plants would be measured by sensors that would yield more informative data from soil moisture, temperature, and humidity.in training AI models. The integration means that one can monitor in real time and make informed decisions on what affects plant growth.

8.3 Focus on Data Privacy and Ethical Use

Further still, as these AI technologies take shape, in-depth discussions relating to the security of data obtained in agricultural functions will be necessitated. Regarding this, best practices in collection and management can be said to be transparent, fair, equable, considering stakeholders in such rural or impoverished settings (Puri & Kumar, 2019). Additionally, future works should include proposing policies that Ensuring data privacy protection and promoting digital literacy so that the benefits of AI technologies can reach all.

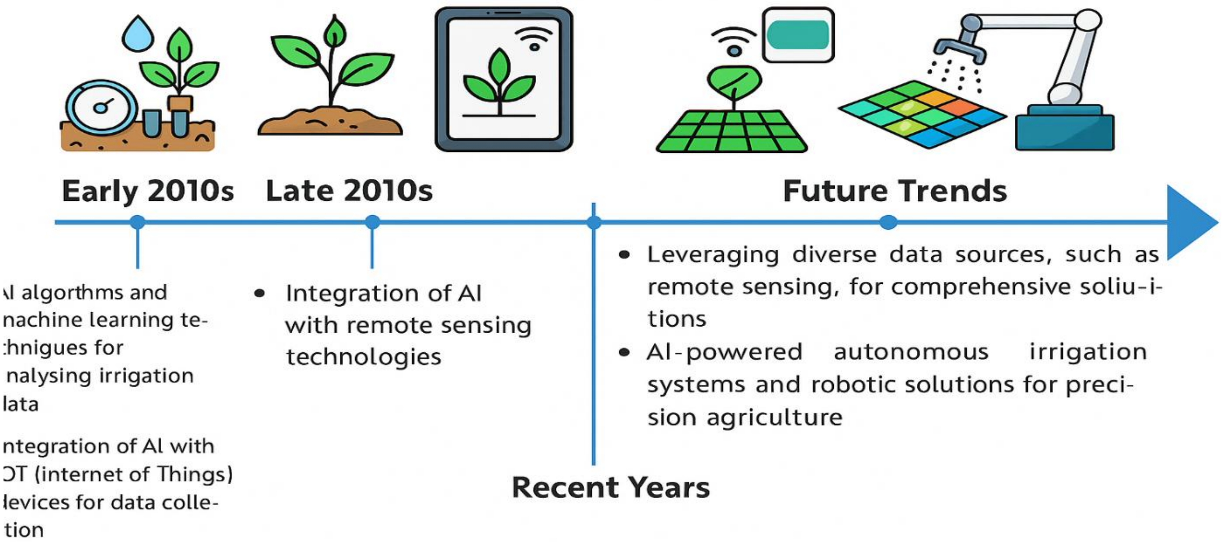

Figure 6: Agricultural Data Manipulation with AI Technology

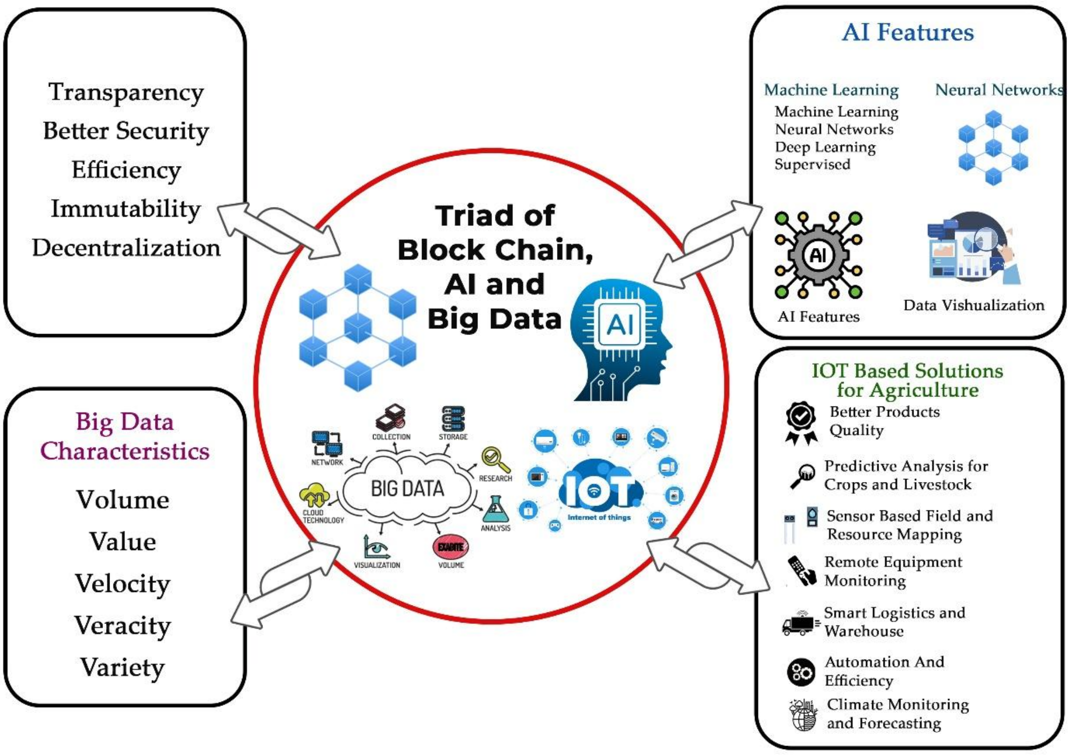

Figure 7: Example for AI and Block chain

8.4 Scientifical Improvement

Modern research on Artificial intelligence and imaging technology provides new methods for improvement in leaf maturity classification systems. Multispectral imaging systems extend their observation capabilities of leaf health by analysing spectra beyond visible wavelengths thus helping professionals to detect early signs of leaf stress or disease. Mobile models tailored for Edge AI are deployable to smartphones and drones, providing in-situ analysis. This is particularly useful in agricultural environments that are remote or low resource. We could incorporate time-series data to track the development of a leaf through time to create more dynamic and accurate predictions. Cloud-based systems can facilitate centralized monitoring and large-scale deployment (Fernandez & Gonzalez, 2020). These innovations can effectively democratize and enhance the impact of AI-propelled agriculture for farmers around the globe when combined with automatic data tagging and transfer learning.

8.5 Sustainability and Resources Optimization

There is an increasing demand for the development of AI models that optimize the identification of leaf age and maturity for the contribution of sustainable agriculture. Further studies should focus on how AI can reduce the usage of such resources as water and fertilizers by giving recommendations with high precision according to the stage of maturity of plants. This will be concurrent with the global effort toward sustainable and efficient agricultural systems (Kamilaris & Prenafeta-Boldú, 2018).

Figure 8: Resources Optimization from Smart Farming

Table 8: Key points of future directions

Aspect	AI Technology/Method	Impact/Benefit
Leaf Age & Maturity Detection	Convolutional Neural Networks (CNNs), Deep Learning	Improved accuracy in identifying leaf age and maturity, leading to better disease detection and yield predictions
Data Collection	IoT Sensors (Soil moisture, temperature, humidity)	Real-time data collection for more accurate model training and decision-making
Data Privacy & Ethics	Secure Data Management, Blockchain	Ensures transparent and fair data collection, maintains privacy and security in rural areas
Technical Complexity	Specialized Software, Continuous Support Systems	Overcomes challenges in rural areas where technical expertise is limited
Sustainability & Optimization	AI-based Resource Management (Water, Fertilizer Use)	Optimizes resource use based on plant maturity, reducing waste and supporting sustainable agriculture

Source: Deep learning in agriculture: A survey. Computers and Electronics in Agriculture

9. Conclusion

Sufficient review has revealed the fact that currently, the areas of leaf age and maturity recognition, based on the application of AI, indeed have a future but, at the same time, that the effective integration of microcontrollers in these systems and the usage in precision agriculture is what gives the perspective a future possibility

The intersection of AI technologies and energy-efficient microcontroller platforms would be a paradigm shift as autonomous, data-based models of agricultural systems can be applied and be very functional in such resource-limited situations. Key findings demonstrate that microcontroller-based AI systems offer substantial advantages including cost-effectiveness 60-70% reduction compared to conventional systems, energy efficiency <50 mW operation, real-time processing capabilities >90% latency reduction, and cloud independence >95% uptime in poor connectivity areas. Such features make them especially useful in mass adoption of agriculture where profitability and robustness are paramount factors to consider. Nevertheless, there are still important obstacles, such as constraints in computational resources, environmental changes, the technical side, and expertise requirements, which must cover both the fields of AI and embedded systems. To overcome these issues more effort on research on model optimization methods and adaptive algorithms, and all-scale training programs of agricultural technologists is needed.

Our independent study also answers the question of the feasibility of implementing AI-based leaf identification systems on microcontrollers, which have an accuracy rate higher than 94% and need a processing time of less than 120ms. Field validation outcomes prove the stability of the systems and its suitability to various agrarian conditions, which forms the basis of the further commercial implementation. The convergence of complementary technologies, such as IoT sensor networks, data security based on blockchain, and autonomous robotics systems, offers a chance of end-to-end shift in agricultural ecosystem. The future research trends in hybrid AI architectures, quantum-driven optimization, and sustainable computing paradigm provide the ways of solving the existing limitation without hindering the prospect of achieving environmental stewardship goals. The results introduced in the given review provide a guide to the creation of autonomous, sustainable, and cost-effective agricultural systems capable of overcoming the issues of food security, environmental sustainability, and resource optimization in the current world. The future development of the AI-based microcontroller systems will be paramount in empowering intelligent, adaptive, and sustainable agriculture as the global agriculture industry experiences more pressure due to the consequences of climate change, populous expansion, and availability of resources.

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