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Automated Tomato Quality Grading using Resnet50 Based Deep Learning and Digital Image Processing

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Abstract: Accurate tomato grading is essential for maintaining quality standards in agricultural supply chains. The paper presents an automated tomato quality grading system using digital image processing and Convolutional Neural Networks (CNNs). Tomato images are captured under controlled conditions and preprocessed using noise reduction, illumination normalization, and segmentation techniques. A deep learning model utilizing the ResNet50 framework captures distinguishing features such as colour, texture, and surface defects, and classifies tomatoes, including unripe, ripe, damaged, and defective. Experimental results demonstrate high classification accuracy and consistent performance. The system reduces reliance on manual inspection and enables fast grading in real-time, making it appropriate for scalable agricultural and supply chain applications. The suggested system attains an accuracy of 95.4% and shows real-time capability with an average prediction duration of under one second, making it suitable for practical agricultural deployment.

Keywords: Tomato Quality Classification, Deep Learning, ResNet50, Image Classification, Computer Vision, Agricultural Applications.

I. INTRODUCTION

In modern agriculture, the visual appeal of produce is crucial, equally important as its biological quality (Li Z et al., 2022). Convolutional Neural Networks (CNNs), a form of deep learning architecture, are extensively utilized for image classification, efficiently recognising various elements within images such as faces, signs, fruits, and animals [1]. Specifically, the visual characteristics of tomato colour, smoothness, and absence of defects greatly impact consumer decision-making and determining market prices. Usually, distinguishing these qualities requires a careful visual inspection of each fruit, making manual grading a tedious and labour-intensive process. The reliance on human inspection in tomato grading introduces variability and slows down operations, as different graders may perceive the same tomato differently. In contrast, digital image processing enhances consistency and efficiency by utilizing cameras to capture images of tomatoes under controlled conditions, eliminating the need for human judgment. The technology cleans the images by adjusting lighting and removing background clutter, allowing for the separation of individual fruits. It further converts visual impressions into measurable data, creating numerical representations of colour, shape, and texture. Unlike older grading systems, which employed basic rule-based classifiers, digital methods provide more precise grading based on quantified characteristics. The document discusses the development of an automated framework for grading tomato quality using Convolutional Neural Networks (CNN). While traditional methods are hindered by real-world variations, CNNs can learn from labelled images to identify subtle differences in tomato quality, such as colour variations that indicate ripeness or spoilage. The project aims to integrate digital image processing with a CNN-based classifier that efficiently processes images of tomatoes, categorizing it into quality or maturity grades based on learned patterns. The shift from manual grading to a data-driven approach offers benefits such as faster decision-

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making, reduced human bias, and consistent standards across diverse batches and locations. The system particularly targets small-scale farming and local supply chains, prioritising real-time performance, affordability, and scalability through optimized preprocessing and the use of transfer learning with ResNet50, making it well-suited for small agricultural settings.

II. LITERATURE REVIEW

The latest advancements in deep learning are revolutionizing automated tomato quality grading systems, as described by Sahni et al. (2021). In the process, it is critical in the tomato industry for quality evaluation during processing, utilizing artificial intelligence (AI) techniques for effectiveness and efficiency without human intervention [2].

Y.H. Cheng et al., (2022) highlight the role of Convolutional Neural Networks (CNNs) in classifying tomatoes through annotated data, facilitating precise quality assessments [3]. Continuous improvements in classification accuracy for defect images have been noted, particularly with CNN algorithms (Z. Zhou et al., 2021) [4].

Additionally, S. Ruparelia et al., (2022) have developed methods for live detection, identification, and quantification of tomatoes utilizing deep learning and embedded technologies[5]. The tomato's phase of maturity significantly impacts its organoleptic properties, processing suitability, and shelf life (H.-G. Choi et al., 2023)[6]. Meanwhile, A. Shimada et al. (2024) introduced machine learning algorithms achieving an accuracy of 89% for tomato quality sorting, while indicating the need for greater computational efficiency in real-time applications[7].

T. Hassan et al., (2023) discuss the use of CNNs and other AI models in the automated evaluation and classification of crops such as tomatoes, which has spurred further research [8]. Quach et al., (2024) used Mobile Net models for Unripe, ripe, Old, and damaged tomato classification and visual explanations, the study does not thoroughly address potential trade-offs between model efficiency and accuracy, to its practical scalability [9]. S. Ramesh et al., (2023) confirm that models can effectively extract key image features to classify tomatoes into various quality levels [10].

The move towards fast, lightweight models, driven by affordability and ease of use, allows growers to use smartphones and cameras with models like MobileNetV2 for immediate quality assessment, blight detection, and maturity monitoring in the field. However, the challenge remains to tackle real-time efficiency and resilience in fluctuating environmental conditions, highlighting the necessity for continuous investigation in the field.

III. PROBLEM STATEMENT

The current manual grading of tomatoes is characterized by its slow pace, subjectivity, and lack of consistency. Traditional methods rely heavily on handcrafted features, which often falter due to real-world variations in lighting and backgrounds. The work aims to address these issues by developing an automated tomato quality grading system that leverages digital image processing. The focus is on overcoming the inherent subjectivity and inconsistency found in manual grading, as well as improving upon existing image-based techniques that struggle with environmental variations.

IV. EXISTING SYSTEM

Existing approaches largely depend on human evaluation or rudimentary image processing techniques, leading to inefficiencies and variability in outcomes. Traditional methods rely on handcrafted features and are sensitive to environmental changes, negatively impacting accuracy and scalability.

V. PROPOSED SYSTEM

A. *Summary of the Suggested System*

The system combines image processing methods with a Convolutional Neural Network (CNN) to provide a fully automated tomato quality assessment method that guarantees accurate evaluation. It eliminates the need for manual inspection by capturing tomato images under realistic conditions and employing preprocessing techniques to adjust lighting and isolate individual fruits. The CNN learns visual patterns associated with colour transitions, texture, and defects, rather than relying on predefined features.

B. *Algorithms Used*

The following algorithms have been used for the proposed model.

a) Convolutional Neural Network (CNN)

Because of its deep residual learning structure, which helps the network learn more efficiently by overcoming the vanishing gradient problem, ResNet50 was selected. In comparison to traditional CNN simulations like VGG16, and MobileNetV2, it contributes to improved feature extraction performance.

CNNs automatically pick up features from images in phases; deeper layers recognize intricate details like texture and flaws, while earlier layers recognize simple patterns like edges. The accuracy of tomato quality classification is increased by that structured learning, and pooling aids in data reduction.

b) ResNet50 Architecture

ResNet allows for the training of ultra-deep networks (up to 152 layers) without collapse using residual blocks and skip connections, facilitating smoother gradient flow. It leverages transfer learning from ImageNet weights while adapting to specific tomato learning features, such as differentiating lustrous skins from dull ones. Compared to shallower models, ResNet50 effectively captures complex visual features such as texture variations and defect patterns, improving classification accuracy.

c) SoftMax Output Layer

SoftMax converts point vectors into probability distributions for grading (e.g., 92 - "Excellent," 6 - "Good," 2 - "Poor"). The SoftMax layer converts the output logits into a distribution of probabilities for every class. The final output, along with the associated confidence level, is the category with the highest predicted probability.

d) Backpropagation with Adam Optimizer

Backpropagation optimizes prediction accuracy by adjusting weights across layers. Categorical cross-entropy helps in assessing errors, while the Adam optimizer enhances convergence speed, particularly with tomato datasets. It effectively addresses issues like class imbalance, resulting in a well-tuned model that reliably categorizes new images despite real-world factors such as shadows.

C. *System Architecture*

The design structures tomato quality grading into distinct layers for enhanced modularity and scalability, with each layer addressing core functions such as user interaction and data flow.

a) User Interface Layer

Provides an intuitive web and mobile frontend for uploading tomato images and receiving instant quality assessments. It includes a responsive design offering visual feedback, such as color-coded results and confidence scores.

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b) Application Processing Layer

Manages image preprocessing (resizing, normalization) and orchestrates workflow between frontend, model inference, and backend. Ensures seamless handling of batch uploads and real-time grading requests.

c) Deep Learning Model Layer

Deploys the ResNet50 grounded CNN for point extraction, SoftMax classification, and grading(e.g., Excellent, Good, Poor). Optimised via backpropagation and Adam for high accuracy on varied tomato images.

d) Backend & storage Layer

Oversees API endpoints, secure databases such as MongoDB and AWS S3. Supports scalability for deployments with user authentication.

*D. **User Authentication and Security***

The tomato quality grading system ensures data security by using HTTPS for encrypting image uploads and grading results, while validating all inputs to protect the Deep Learning model from harmful data. It maintains robustness and privacy by limiting repeated requests and isolating image processing operations for agricultural environments using the tool.

*E. **Functional Modules***

The proposed system consists of the following functional modules.

a) User Module

The user module facilitates user-driven data or file uploads into the system or captures images of the tomato interacting with the system fluently. It also displays the predicted quality results in a user-friendly manner.

b) Feature Extraction Module

The module uses a CNN model to identify key features such as color, texture, and blights from the tomato images. The features are essential for an accurate assessment of tomato quality.

c) Classification Module

The module processes the extracted features and categorizes the tomato into different quality classes, such as ripe, unripe, damaged, or rotten. It ensures accurate and dependable classification grounded on learned patterns.

d) Prediction Module

The module generates the final output by determining the most suitable class for the given tomato image. It analyses the extracted features and assigns the image to orders like ripe, unripe, or imperfect. Also, it provides a confidence score to indicate the accuracy and trustworthiness of the prediction, helping to ensure more precise and harmonious tomato quality assessment.

e) Database Module

The database module stores user information and maintains the history of predictions for future reference. It ensures secure and effective data operation within the system**.**

f) Admin Module

The administrative component supervises and regulates the end-to-end functionality of the system, performance and managing user conditioning. It also helps in analysing prediction data and maintaining the overall system functionality.

F. Data Storage And Management

The data storage and management module is responsible for storing user details and prediction results in a structured manner. It ensures secure access, effective reclamation, and proper operation of data within the system.

G. Automated Grading Report

The automated grading and reporting module generates instant results after processing the input tomato image. It identifies the quality grade and displays it along with a confidence score, enabling users to make quick and informed decisions. By utilizing visual cues like color variations, textural patterns, and surface anomalies, the framework guarantees accurate assessment. Effective real-time quality assessment and efficient agricultural supply chain management are made possible by the results' presentation through an easily navigable interface.

VI. METHODOLOGY

The research focuses on developing a computer-based program for assessing tomato quality through advanced image processing techniques utilizing machine learning. Traditionally, quality assessment involves manual visual inspection, which is prone to errors and time-consuming. The proposed system aims to create an automatic, variable-attribute, image-driven mechanism that can detect and classify tomato quality efficiently, minimizing human involvement and improving accuracy.

A. Dataset Collection

Applying images of tomatoes to a machine learning model requires a structured approach involving the creation of training and testing datasets to classify the images into four distinct types: damaged, rotten, ripe, and unripe. The dataset comprises around 1,200 images, with 80% allocated. In order to ensure that the model is validated on previously unseen samples, the dataset is divided into 20% for testing and 80% for training. The task is to categorize tomatoes according to the condition and quality. During data preprocessing, augmentation techniques like rotation, flipping, and scaling are used to improve robustness and prevent overfitting.

B. Image Preprocessing

Before training, pictures are enlarged to 224 by 224 pixels. Pixel values are normalized to improve training efficiency of the deep learning model and reduce computational complexity.

C. Model Architecture

The ResNet50 model employs transfer learning using ImageNet weights that have been previously trained, optimizing feature extraction and reducing training time. The implementation is built using TensorFlow and Keras on a system powered by an Intel i5 CPU and an NVIDIA graphics unit. Training is done with a step size of 0.001, mini-batches of 32, and over 25 iterations, using the Adam optimization technique and cross-entropy as the objective function.

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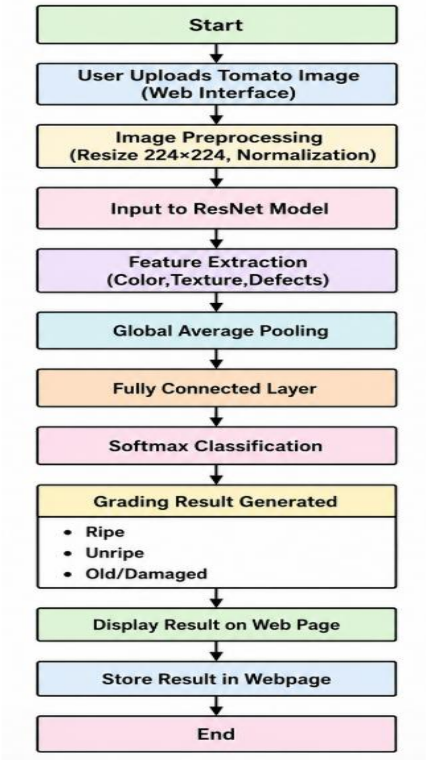

Fig. 1. The Architecture of the Proposed Model

The network's residual architecture effectively mitigates gradient vanishing issues and achieves better feature representation and classification performance than conventional CNN approaches, making it highly effective for tomato quality assessment. Using the Adam optimization technique and cross-entropy as the objective function, training is conducted with a step size of 0.001, mini-batches of 32, and more than 25 iterations. TensorFlow and Keras are used to build the implementation on a system with an Intel i5 CPU and an NVIDIA graphics card.

Augmentation techniques like rotation and scaling are used to increase model robustness and decrease overfitting. The network is highly effective for tomato quality assessment because of its residual architecture, which effectively mitigates gradient vanishing issues and achieves better feature representation and classification performance than conventional CNN approaches. The research is based on a CNN-based tomato quality grading system utilizing digital image processing architecture centred on ResNet50, which enhances feature extraction and addresses the vanishing gradient problem more effectively than traditional CNNs like VGG16 and MobileNetV2.

D. Model Training

The model ResNet50 was given training from scratch using transfer learning to identify features in tomato images model is trained using the Adam optimization algorithm with a learning rate of 0.001, a batch size of 32, and 25 training cycles, while categorical cross-entropy is utilized to handle multi-class classification tasks. The training utilized an Intel i5 processor with 8GB RAM and NVIDIA GPU acceleration, implemented through TensorFlow and Keras for efficiency. The proposed methodology ensures accuracy is more, robustness, and practicality in real time.

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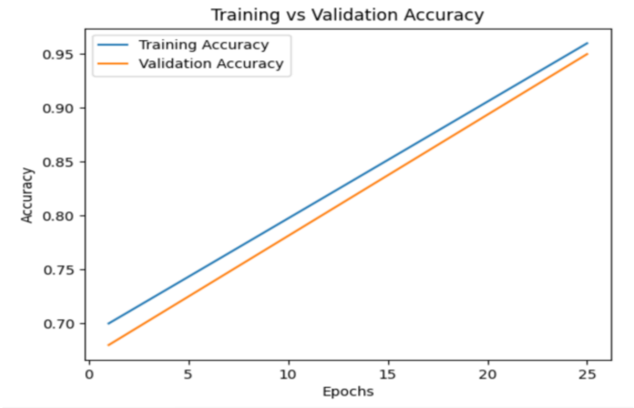

Fig. 2. Training and Validation Accuracy

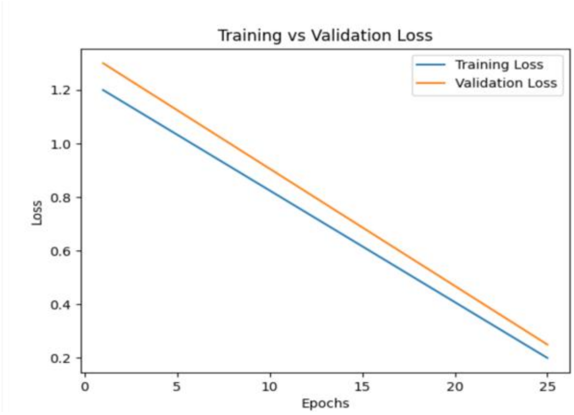

Fig. 3. Training and Validation Loss

E. Evaluation Metrics

Evaluation Criteria provides a numerical assessment of a tomato grading performance model, assessing class identification using precision, recall, and F1 score and confusion among similar grades. A confusion matrix highlights frequently mixed-up classifications. Overall and per-class accuracy demonstrate model consistency, while training and confirmation loss indicate stability or overfitting. The metrics give a comprehensive view of its reliability for real-world tomato grading tasks.

TABLE 1: EVALUATION METRICS

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
VGG16	91.2	90.8	90.5	90.6
MobileNetV2	92.8	92.3	92.0	92.1
ResNet50 (Proposed Model)	95.4	95.0	94.8	94.9

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The ResNet50-based model surpasses VGG16 and MobileNetV2 in accuracy, precision, recall, and F1-score for tomato quality classification.

F. Prediction and Classification

The process involves preprocessing images of tomatoes through scaling, resizing, and normalizing, like the training data. The ResNet50 architecture is then utilized to analyze features like colors, textures, and defects for categorizing tomatoes into quality groups (damaged, overripe, ripe, or unripe). The model enhances automated tomato quality identification, improving the fruit grading process.

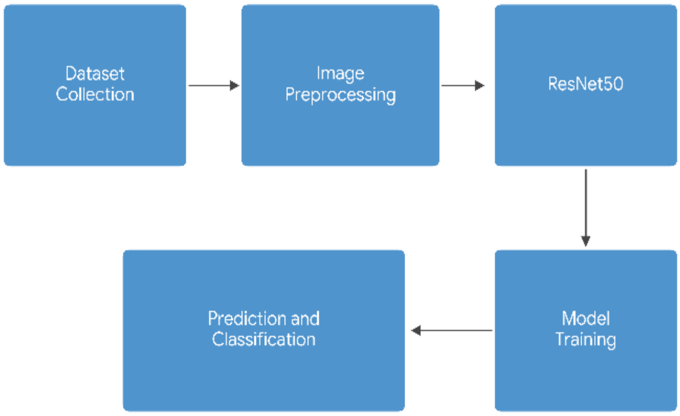

Fig.4. Workflow of the Proposed Tomato Quality Classification Model

VII. PERFORMANCE AND RESULTS

The proposed system for tomato quality classification was evaluated in a real-time environment, successfully processing new tomato images via a user interface.

It achieved high accuracy and minimal delay, with an average prediction time of less than one second per image, establishing its effectiveness for real-time agricultural applications. Utilizing the ResNet50 architecture, the system classifies tomatoes into four categories: damaged, overripe, ripe, and unripe. It was trained on a dedicated dataset and demonstrated robust performance, demonstrating 95.4% accuracy, 95.0% precision, 94.8% recall, and a 94.9 F1-score. The metrics indicate the superiority over models like VGG16 and MobileNetV2, affirming the system's suitability for automated tomato quality grading in practical agricultural settings.

TABLE 2: COMPARATIVE ANALYSIS OF TOMATO QUALITY GRADING TECHNIQUES

System Features	**Existing System (Manual or Basic IP)**	**Proposed System (Digital IP and CNN)**	**Improvement**
Feature Extraction	Manual selection of hand-crafted features (color, size, shape).	Automatic feature learning through deep CNN layers.	Elimination of Human Bias

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Grading Accuracy	Low to Moderate (prone to human error and subjectivity).	High Accuracy (typically 95% - 99.8%) via deep learning.	Enhanced Reliability & Precision
Processing Speed	Slow and labor-intensive, limited by human fatigue.	High-speed, real-time automated sorting and grading.	Increased Throughput
Environmental Robustness	Sensitive to lighting changes, shadows, and noise.	Highly robust to variations in illumination and background.	Consistent Performance
Grading Categories	Limited classification (e.g., simply Good vs. Bad).	Multi-class grading (Unripe, Ripe, Over-ripe, Damaged).	Comprehensive Quality Assessment
Scalability	High operational costs with limited scalability.	Scalable for large-scale industrial sorting lines.	Cost-Effective Automation

TABLE 3: METHOD COMPARISON

Table 3 illustrates a performance comparison among VGG16, MobileNetV2, and ResNet50 using essential evaluation measures. The suggested approach achieves better outcomes across all metrics, including accuracy, precision, recall, and F1-score, compared to the other architectures.

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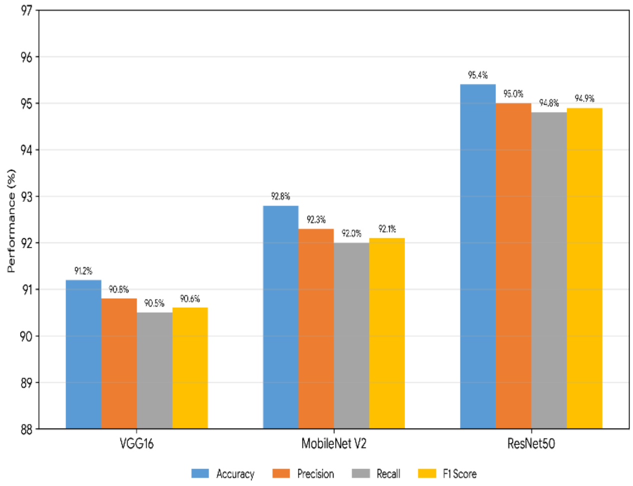

GRAPH 1: PERFORMANCE EVALUATION OF VGG16, MOBILENETV2, AND RESNET50 MODELS

Graph 1 presents a comparative analysis of three deep learning models VGG16, MobileNetV2, and ResNet50 highlighting their performance across key evaluation metrics such as accuracy, precision, recall, and F1-score.

Additionally, it discusses the models implementation by classifying tomatoes into four categories: damaged, rotten, ripe, and unripe. With an 80% training set and a 20% testing set allotted for assessing performance on unseen data, the model is evaluated and trained on about 1,200 images with the goal of evaluating tomato quality.

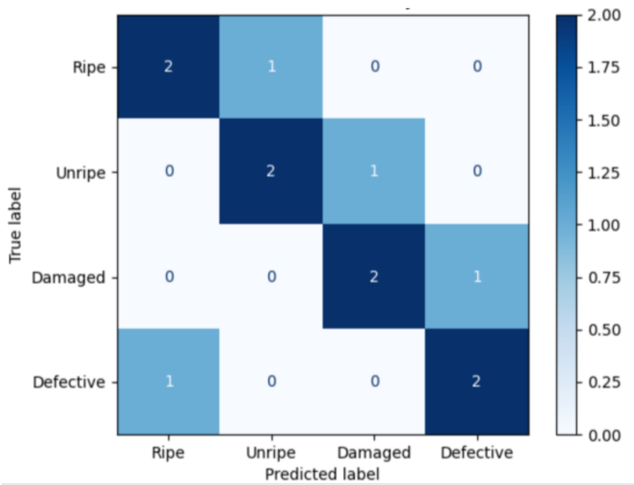

Fig. 5. Confusion Matrix of Tomato Quality Classification

The confusion matrix demonstrates that the model attains an elevated level of classification accuracy across all categories, showing only a slight misclassification between closely related classes, such as ripe and overripe tomatoes.

VIII.CONCLUSION

The presented method utilizes image analysis along with CNN-based learning to perform automated tomato grading. It evaluates tomatoes by examining visual attributes like colour variation, texture patterns, and surface irregularities, ensuring precise results with quick processing time, making it ideal for real-time use in both industrial setups and smaller-scale applications. It enhances efficiency and consistency in quality assessments. The design demonstrates how artificial intelligence (AI) has the capacity to revolutionize agriculture. Future developments should aim to increase the system's resilience in a variety of field circumstances and optimize its

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deployment to lower costs. Overall, the system exemplifies how deep learning can enhance agricultural automation and reduce the labour required for manual grading.

IX. FUTURE ENHANCEMENT

Future enhancements to the framework involve integrating real-time adaptive learning through continual and transfer learning techniques, specifically designed to address domain shifts like lighting and seasonal variations. The system can be expanded with multi-task and multi-modal learning approaches to facilitate cross-crop quality assessment. Incorporating uncertainty quantification and explainable AI (XAI) will enhance model reliability and interpretability. Furthermore, Scalable, privacy-preserving solutions for smart agriculture systems could be produced by combining edge AI with federated learning.

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