



Digital Twin-Driven Crop Growth Monitoring System Integrated with Deep Learning-Based Disease and Quality Assessment

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Abstract. Recent advances in artificial intelligence have led to the development of systems that can interpret visual agricultural data and support decision-making at various stages of crop growth. This paper presents an integrated plant intelligence framework that combines structured JSON-based crop knowledge modeling, deep learning-based visual analytics, and a digital twin-driven method for tracking growth over time, all within a single mobile application. The system workflow starts with user-captured crop images. These images undergo preprocessing and are analyzed using deep learning architectures, including Custom Convolutional Neural Networks (CNN), EfficientNet, and ResNet, which have been tested experimentally. The analysis focuses on growth stage classification, disease detection, and fruit quality assessment. The predicted outputs are combined with user-provided planting timelines and specific agronomic growth rules. This integration creates a dynamic digital twin representation of crop development, allowing for visualization and monitoring throughout the lifecycle. Experimental evaluations show that the ResNet-based disease detection model achieved a classification accuracy of 92%, better than CNN at 78% and EfficientNet at 91%. The fruit quality assessment model reached a peak accuracy of 98%. These results demonstrate the effectiveness of pairing vision-based prediction with growth simulation to improve understanding and practical decision making. The modular design of the framework allows it to scale across various crops. It also supports real-world agricultural monitoring through an easy-to-use mobile interface.

Keywords: Digital Twin, Deep Learning, Computer Vision, Crop Growth Monitoring, Disease Detection, Digital Agriculture.

1 Introduction

Agricultural productivity is increasingly affected by environmental uncertainties like climate changes, pest and disease outbreaks, soil degradation, and inefficient use of water and nutrients. These challenges require smart monitoring solutions that can provide timely insights for effective crop management. Recent advancements in artificial intelligence (AI) and deep learning (DL) have led to automated agricultural applications, including crop disease detection, fruit quality assessment, and yield prediction. However, many current systems handle these tasks separately and offer static predictions that do not consider the entire lifecycle of crop growth.

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In real farming situations, decision-making needs ongoing interpretation of crop conditions instead of just looking at one growth stage. Vision-based crop analysis models often identify diseases or plant conditions from images without factoring in the growth behavior over time. This can make the results hard to understand in actual management contexts. Additionally, the lack of organized agronomic knowledge representation and lifecycle-aware modeling lowers user trust and limits the practical use of AI-driven crop advisory systems. To address these issues, this work proposes an integrated plant intelligence framework that merges structured crop knowledge representation, deep learning-based visual analysis, and digital twin-driven growth tracking in a single decision-support environment. The digital twin part offers a lightweight virtual representation of crop development by combining planting timeline inputs, predicted growth stages, and defined agronomic growth rules. This allows for intuitive visualization of past, present, and expected crop growth states without needing continuous sensor infrastructure.

For automated crop condition analysis, several deep learning architectures, including Convolutional Neural Networks (CNN), EfficientNet, and ResNet, are evaluated for tasks like growth stage classification, disease detection, and fruit ripeness assessment. The combination of these predictive models with lifecycle-aware digital twin visualization improves interpretability and aids in making better agricultural decisions. All functional modules are implemented in a Flutter-based mobile application, providing an easy-to-use platform for real-time crop monitoring, knowledge exploration, and recommendation support. The rest of this paper is organized as follows. Section II reviews related work on digital twin concepts and AI-driven crop monitoring methods. Section III describes the proposed methodology and system architecture. Section IV discusses experimental evaluation procedures and performance metrics. Section V presents results and discussion, while Section VI concludes the paper with possible future research directions.

2 Literature Survey

Contemporary agriculture is increasingly adopting intelligent monitoring systems to improve crop growth analysis, disease management, and yield optimization. However, many existing solutions address individual agricultural tasks independently, such as sensor-based environmental monitoring, image-based disease detection, or simulation-driven crop modelling. As a result, these systems often fail to provide a comprehensive lifecycle-oriented understanding of crop development that is essential for practical farm decision-making. In particular, there is limited integration of vision-driven crop analysis, temporal growth modelling through digital twin concepts, structured agronomic knowledge representation, and context-aware recommendation support within a single intelligent framework.

IoT-based smart agriculture systems combined with blockchain technologies have been proposed to enhance secure data acquisition and improve transparency in agricultural monitoring infrastructures [1]. While such approaches strengthen data reliability and enable distributed sensing, they primarily focus on infrastructure-level monitoring

and do not incorporate visual crop condition analysis or growth stage interpretation. Consequently, their applicability remains limited in scenarios requiring plant-level lifecycle monitoring and predictive decision support.

Research on machine learning approaches for plant disease forecasting provides valuable insights into algorithmic techniques for crop health prediction [2]. However, many of these studies rely on structured datasets or statistical modelling approaches without integrating real-time visual inference or growth stage contextualization. This restricts their ability to support dynamic crop monitoring across different developmental phases.

Digital twin concepts have recently emerged as a promising paradigm for modelling crop growth behavior and enabling predictive agricultural analytics. Studies exploring digital twin applications in crop monitoring demonstrate the potential of virtual crop representations for simulation-based decision support [3], [4]. Nevertheless, several implementations remain conceptual or depend heavily on continuous sensor data streams, limiting their scalability and accessibility in practical farming environments. Other research has investigated digital twin-based disease monitoring and nutrient balance analysis for specific crop attributes [5]. Although these approaches contribute to precision observation, they do not provide integrated lifecycle-aware monitoring combined with vision-based analytics and adaptive advisory generation.

In the computer vision domain, deep learning models have achieved strong performance in plant disease recognition and post-harvest fruit quality classification tasks [6][7][8]. These studies validate the effectiveness of convolutional architectures for agricultural image analysis; however, they typically focus on isolated classification problems without embedding predictions within temporal crop growth contexts. Knowledge-based crop recognition approaches further highlight the importance of structured agronomic information for improving interpretability and usability [9], yet such systems often lack dynamic growth modelling capabilities and integrated visualization mechanisms.

From the analysis of existing literature, it can be observed that limited research has addressed the development of an end-to-end agricultural intelligence system that integrates structured crop knowledge, deep learning-based visual prediction, and digital twin-driven lifecycle growth modelling within a unified decision-support platform. The proposed framework aims to bridge this research gap by enabling continuous visual crop analysis, lightweight temporal growth simulation, and context-aware recommendation generation. This integrated approach facilitates scalable, interpretable, and practical crop monitoring solutions capable of supporting informed decision-making under dynamically changing agricultural conditions.

3 Methodology

This section describes the design and implementation of the proposed intelligent crop monitoring framework, which integrates structured crop knowledge modelling, digital twin-based growth tracking, deep learning-driven disease detection, and fruit quality assessment within a unified decision-support system. The framework follows a modular

multi-task architecture in which individual analytical components operate independently while collectively contributing to lifecycle-aware crop monitoring. The overall workflow begins with user-captured crop images that undergo preprocessing operations such as resizing and normalization before being analyzed using deep learning models. The prediction outputs are subsequently integrated with temporal crop growth information to generate dynamic digital twin visualizations and actionable recommendations through the mobile application interface.

3.1 Crop Knowledge Modelling and Representation

A structured crop knowledge representation model was developed using a standardized JSON-based schema to capture comprehensive crop-specific agronomic information in a reusable and machine-readable format shown in Fig.1. The schema incorporates attributes such as climatic requirements, irrigation practices, fertilizer schedules, pest and disease profiles, expected yield ranges, geographical suitability, and harvest duration. This structured representation facilitates consistent storage, retrieval, and visualization of crop knowledge within the mobile application environment.

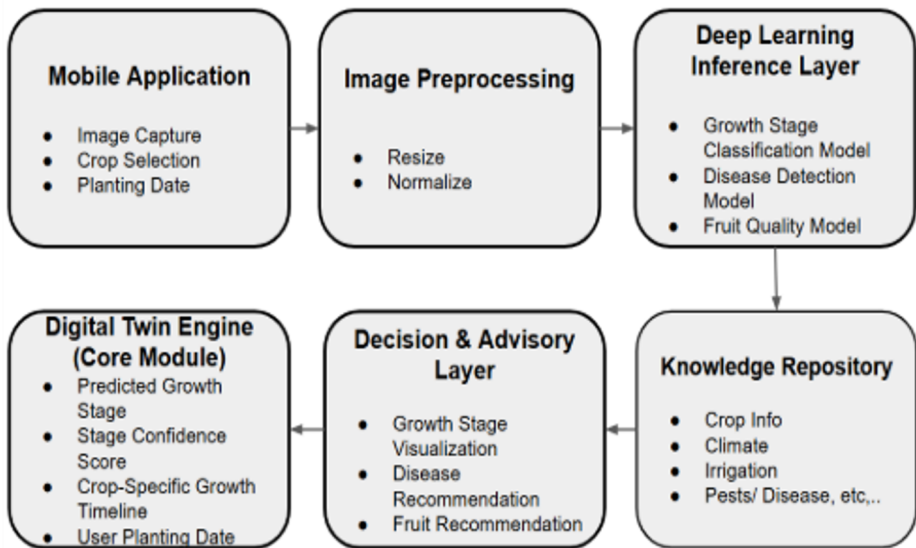


Fig. 1. Overall system architecture of the proposed framework.

Furthermore, the modular schema design enables scalability and seamless extension across multiple crop varieties without altering the underlying system architecture. Table 1 presents the unified JSON schema formulated for structured crop knowledge modelling.

Table 1. Standardized crop knowledge JSON schema.

JSON Key	Description	Data Type
Name	Common name of the crop	String
scientific_name	Botanical name	String
crop_type	Crop Category	String
region_and_uses	Regions of cultivation and primary uses	Object (List)
climate_and_season_requirement	Climate, Temperature, rainfall requirements	Object
fertilizer_schedule	Nutrient demand and fertilizer practices	Object
irrigation_practice	Water requirement and irrigation methods	Object
pests_and_diseases	Common pests and diseases	Object
yield_range	Expected yield under good management	Object
harvest_duration	Crop duration and harvest details	Object
regional_variants	Popular regional variants	List

3.2 Digital Twin-Based Growth Tracking

The digital twin module provides a temporal representation of crop growth behaviour by integrating image-based growth stage predictions with predefined agronomic growth progression rules. Unlike conventional systems that generate isolated stage predictions, the proposed module enables continuous simulation and visualization of crop development over time. This temporal modelling capability supports lifecycle-aware monitoring and enhances interpretability of crop condition assessments within real-world agricultural scenarios.

Growth Stage Dataset Preparation: For growth stage monitoring, image datasets were collected for three crops: tomato, cucumber, and chilli. The datasets were systematically categorized into key developmental phases, namely early vegetative stage, flowering initiation stage, and fruiting stage.

Table 2. Growth stage dataset composition for digital twin tracking

Crop	Growth Stages Considered	Images per Stages
Tomato	Early vegetative, Flowering initiation, Fruiting	~ 400 images
Cucumber	Early vegetative, Flowering initiation, Fruiting	~ 400 images
Chilli	Early vegetative, Flowering initiation, Fruiting	~ 2000 images

These stages were selected as they represent visually distinguishable transitions in plant growth, thereby improving classification reliability. Images were sourced from publicly

available agricultural repositories and manually curated to ensure stage-level consistency and minimize label ambiguity. The curated dataset composition used for training the growth stage prediction models is summarized in Table 2.

Growth Stage Classification Model: Growth stage prediction was performed using convolutional neural network (CNN)-based image classification models. Separate classifiers were trained for each crop category to reduce inter-crop visual ambiguity and improve stage recognition accuracy. Input images were resized to a uniform resolution and normalized prior to training. Feature extraction was carried out using stacked convolutional and pooling layers, followed by fully connected layers and softmax activation to generate class probability distributions. During experimentation, multiple deep learning architectures were evaluated, and the best-performing models were incorporated into the digital twin framework. The predicted growth stage along with its associated confidence score serves as the state estimation parameter for digital twin simulation.

- Digital Twin Timeline Generation.

The digital twin engine integrates three primary inputs: user-provided planting date information, predicted growth stage outputs from the classification model, and predefined agronomic growth duration rules for each crop. Based on these parameters, the system generates a dynamic timeline representing past, current, and projected growth stages. This temporal visualization enables intuitive monitoring of crop development and supports proactive agricultural decision-making. An example digital twin timeline visualization for tomato growth stages is illustrated in Fig. 2, highlighting both the current developmental phase and expected future progression. This approach enables continuous crop growth tracking even when image inputs are provided intermittently by the user.



Fig. 2. Digital twin-based growth timeline for tomato, highlighting the current stage and projected future stages

3.3 Crop Disease Detection

The crop disease detection module enables automated identification of plant diseases from input crop images and generates prediction outputs in a decision-support format. Image datasets were curated for multiple crops including banana, tomato, and cucumber, covering both healthy conditions and various disease classes. To ensure a fair architectural comparison, three deep learning models Custom Convolutional Neural Network (CNN), EfficientNet, and ResNet were trained under identical experimental settings. All models utilized uniform input image resolution, normalized preprocessing, consistent optimizer configuration, and the same loss function during training. The trained models classify crop images into disease-specific categories and generate confidence-based probability scores. These predictions are subsequently mapped to predefined advisory modules that provide disease descriptions, preventive strategies, and treatment recommendations to assist users in practical crop management.

3.4 Fruit Ripeness and Quality Assessment

The fruit quality assessment module supports post-harvest decision-making by categorizing produce images based on ripeness and usability conditions. Deep learning architectures including CNN, EfficientNet, and ResNet were trained on datasets containing images of tomatoes, bananas, and chillies labelled into ripeness classes such as unripe, ripe, and overripe or spoiled. Feature extraction from fruit images enables classification into standardized quality states applicable across multiple crop types. Based on the predicted ripeness category, the system generates actionable recommendations related to consumption suitability, storage duration, and post-harvest handling practices, thereby improving produce utilization and reducing wastage.

3.5 Mobile Application Integration

All trained deep learning models were optimized into lightweight inference formats to enable efficient deployment within a Flutter-based mobile application. The application provides functionalities such as real-time image capture, on-device prediction, structured crop knowledge visualization, and interactive digital twin timeline rendering. This integration ensures accessibility, low-latency decision support, and practical usability for farmers and agricultural stakeholders operating in diverse field environments.

4 Experimental Evaluation and Performance

This section presents the experimental evaluation of the proposed multi-module crop intelligence framework. Performance analysis is conducted for the deep learning components including growth stage prediction, crop disease detection, and fruit quality classification using quantitative metrics such as classification accuracy, model confidence scores, and training convergence behavior. The evaluation is performed on curated

multi-crop image datasets under uniform preprocessing and training conditions to ensure fair architectural comparison among Custom CNN, EfficientNet, and ResNet models. In addition, functional validation is carried out for visualization-oriented components such as digital twin timeline generation and structured crop knowledge representation within the mobile application, assessing their effectiveness in supporting lifecycle-aware agricultural decision-making.

4.1 Knowledge Showcase Module

The knowledge showcase module was evaluated based on its ability to provide structured and consistent access to agronomic information across multiple crop categories. The unified JSON-based schema successfully supported knowledge visualization for 20 crop types, enabling systematic retrieval of information related to climatic requirements, irrigation practices, fertilizer schedules, and pest and disease management. Functional validation demonstrated that the structured representation improved interpretability of prediction outputs by providing contextual agricultural insights alongside model-generated results. The mobile interface enabled intuitive navigation through tab-based and card-based layouts, facilitating efficient knowledge exploration and supporting informed decision-making in practical crop management scenarios

4.2 Digital Twin-Based Crop Tracking

Evaluation of the digital twin module has been done based on the outputs of stage prediction and the generation of timelines for tomato, cucumber, and Chilli. The growth stage predictor model classifies the growth stages for a given input image together with a certain level of confidence for each predicted stage. Based on the predicted growth stages of the crops, the user-entered dates of plantation, and the preset stages for a particular crop, the crops undergo dynamic growth stages timeline generation. This analysis confirms the accuracy of growth stages prediction and the timely triggering of the growth stages in the digital twin timelines for the crops. Table 3 describes the outputs of the growth stages prediction of the digital twin.

Table 3. Digital twin stage prediction and timeline generation results

Crop	Predicted Growth Stage	Confidence Score	Timeline Generated
Tomato	Early Vegetative	0.92	Yes
Cucumber	Flowering initiation	0.84	Yes
Chilli	Fruiting	0.94	Yes

The experimental results indicate that the growth stage classification component achieved reliable prediction performance, with confidence scores exceeding 0.80 for all evaluated crop samples. This demonstrates the capability of the trained models to effectively distinguish visually significant developmental stages across multiple crops. By integrating classification outputs with predefined agronomic growth duration rules

and user-provided planting timelines, the digital twin module successfully generated dynamic temporal representations of crop growth. The generated timelines accurately highlighted past, current, and projected growth stages, validating the effectiveness of the proposed approach in transforming static image-based predictions into lifecycle-aware monitoring insights. This temporal modelling capability enhances interpretability and supports proactive crop management decisions without requiring continuous sensor-based observations.

4.3 Crop Detection

Experimental evaluation of the crop disease detection module demonstrated that the ResNet architecture achieved the highest classification accuracy of 92%, outperforming EfficientNet (91%) and the custom CNN model (78%). The superior performance of ResNet can be attributed to its residual learning mechanism, which enables deeper feature extraction and improved gradient flow during training, thereby enhancing generalization across multiple crop disease classes. Training and validation accuracy trends, along with loss convergence patterns, indicate stable learning behaviour and reduced overfitting for the selected model. The use of a unified multi-crop training pipeline further contributed to robust feature learning, enabling consistent disease recognition performance across different crop types under identical experimental conditions

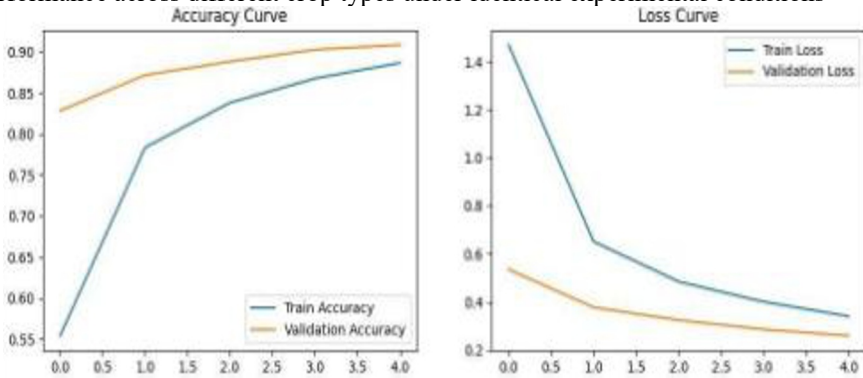


Fig.3. Accuracy and Loss Curves of Disease Detection Model

4.4 Fruit Quality Assessment

For fruit ripeness and quality classification, the ResNet architecture achieved the highest prediction accuracy of 98%, followed by EfficientNet with an accuracy of 97%, while the custom CNN model obtained an accuracy of 94%. The enhanced performance of deeper architectures indicates their effectiveness in capturing subtle visual features associated with texture variation, colour transitions, and surface degradation patterns across ripeness stages. The observed stable convergence behaviour in training and validation curves confirms reliable feature learning and model generalization across multiple fruit categories. From a practical perspective, accurate ripeness classification enables better post-harvest decision-making related to storage planning, consumption

suitability, and supply chain handling, thereby contributing to reduced food waste and improved agricultural resource utilization.

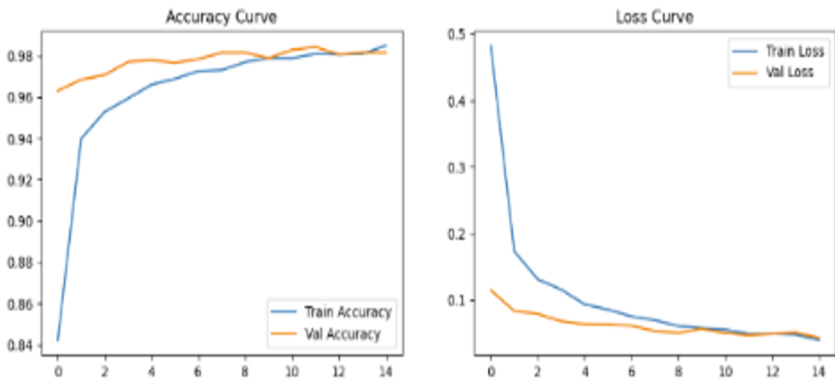


Fig. 4. Accuracy and Loss Curves of Fruit Quality Assessment Model

Overall, experimental evaluation confirms the efficiency of the proposed framework from all aspects of a system. Learning-based modules were trained and evaluated under the same experimental condition, which allows for fair architectural comparison and Model selection. According to the evaluation process, stable training behavior, effective feature learning, and strong generalization capability have been confirmed in both disease detection and fruit quality assessment tasks. Visualization-driven modules are functionally validated regarding correct timeline generation, stage highlighting, and structured information rendering within the mobile application (such as the digital twin and knowledge showcase). These evaluations together provide the basis for solid analysis of system performance and practical applicability, which will be further discussed in the section of results and discussion.

5 Results And Discussion

This section summarizes the integrated performance of the proposed framework across its key modules, including structured crop knowledge visualization, digital twin-based growth tracking, crop disease detection, and fruit quality assessment. The experimental results demonstrate that combining deep learning-based visual prediction with temporal growth modelling improves the interpretability and practical usability of crop monitoring systems.

The knowledge showcase module enabled structured and consistent access to agronomic information for multiple crops through a unified JSON schema and intuitive mobile interface. The digital twin module successfully generated lifecycle-aware growth timelines by integrating predicted growth stages with planting timeline inputs and predefined agronomic rules, supporting continuous crop monitoring without reliance on sensor infrastructure.

In disease detection experiments, the ResNet architecture achieved superior classification accuracy compared to EfficientNet and custom CNN models, indicating improved feature extraction and generalization capability across multi-crop disease datasets. Similarly, high accuracy observed in fruit ripeness classification confirms the

effectiveness of deep convolutional architectures in identifying subtle visual characteristics associated with maturity stages.

Overall, the combined integration of structured knowledge representation, deep learning inference, and digital twin-based temporal visualization provides a scalable and interpretable decision-support framework for intelligent crop management.

6 Conclusion

This work presented an integrated intelligent crop monitoring framework that combines structured crop knowledge representation, digital twin-based growth tracking, deep learning-driven disease detection, and fruit quality assessment within a unified mobile decision-support platform. Experimental evaluation demonstrated that deep convolutional architectures enable reliable visual prediction of crop conditions, while digital twin-based temporal modelling enhances interpretability by contextualizing predictions across the crop growth lifecycle.

The modular system design facilitates scalable knowledge integration and supports practical agricultural decision-making through accessible mobile deployment. Although the proposed framework shows promising performance across multiple analytical tasks, future work may focus on incorporating real-time environmental sensing, adaptive advisory mechanisms, and large-scale field validation to further enhance system robustness and real-world applicability.

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