Growth Monitoring for Fruits Using Computer Vision and Generative AI

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Abstract

This study presents an innovative approach to fruit growth monitoring by integrating computer vision techniques with generative artificial intelligence models. High-resolution images of fruits are captured periodically to analyses size, color, and texture changes over time. Computer vision algorithms enable accurate segmentation and feature extraction, while generative AI models predict growth patterns and simulate future fruit development under varying environmental conditions. This combined methodology enhances precision in growth tracking, supports early detection of anomalies, and optimizes harvest timing, ultimately improving yield quality and agricultural efficiency. The proposed system demonstrates significant potential for automated, non-invasive fruit monitoring in smart farming applications.

Keywords- Fruit Growth Monitoring, Computer Vision, Generative AI, Feature Extraction, Growth Prediction, Precision Agriculture

1. Introduction

Growth monitoring for fruits using computer vision and generative AI is an innovative approach that leverages advanced technologies to enhance agricultural practices. Computer vision enables the automated analysis of fruit size, color, and texture through image processing, allowing for precise and real-time tracking of growth stages. Generative AI complements this by predicting future growth trends, simulating potential outcomes, and generating synthetic data to improve model accuracy. Together, these technologies provide farmers and researchers with powerful tools to optimize crop management, improve yield quality, and reduce manual labor, ultimately contributing to more efficient and sustainable fruit production.

Computer vision, a core branch of AI, uses cameras (RGB, depth, multispectral, and thermal) to capture images of fruits in their natural environment. These images are then processed using deep learning algorithms, particularly (CNNs) and models like YOLO and Faster R-CNN.

Generative AI models, such as Generative Adversarial Networks (GANs), variational autoencoders, and large language models (LLMs), enhance fruit growth monitoring beyond simple analysis by creating new data and solutions.

2. Related Work

Accurate and timely monitoring of fruit growth is essential for optimizing agricultural yield, ensuring quality, and reducing losses [1]. Traditional methods of growth monitoring, which rely on manual inspection and measurement, are labor intensive, error-prone, and often lack scalability. There is a pressing need for an automated, precise, and scalable solution that can continuously track fruit growth stages and detect anomalies early [2].

This research work aims to develop an intelligent system using computer vision to capture and analyses images of fruits over time, combined with generative AI models to predict growth patterns and visualize future development [3]. The system should identify growth metrics such as size, color, and shape, detect diseases or deformities, and generate predictive insights to assist farmers in making informed decisions about harvesting and care [4]

The cultivation of fruits, in particular, requires careful monitoring and management to ensure optimal growth, quality, and yield [5]. Traditional methods of fruit growth monitoring often rely on manual inspection, which can be labor-intensive, time-consuming, and subjective [6].

Computer vision enables the automatic capture and analysis of visual data from fruit crops [7]. By processing images and videos, computer vision systems can objectively measure critical growth parameters including fruit size, color, shape, texture, and the presence of diseases or pests [8]

Manual monitoring of fruit growth is not only labor-intensive but also limits the frequency and scale at which assessments can be conducted. Computer vision systems, equipped with cameras and sensors deployed in orchards or green houses, can continuously monitor large areas without fatigue or downtime [9].

Generative models, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), are emerging tools in agriculture for data augmentation, image enhancement, and synthetic data generation. These models help overcome limitations like small datasets and environmental variability by generating realistic fruit images under different growth stages and conditions. Generative models augment training datasets, improving the robustness of vision-based fruit detection and growth estimation models [1].

Some works use GANs to reconstruct occluded or partially visible fruits for better size and health assessment. Field-deployed vision systems using drones and fixed cameras to monitor fruit size and count over time.

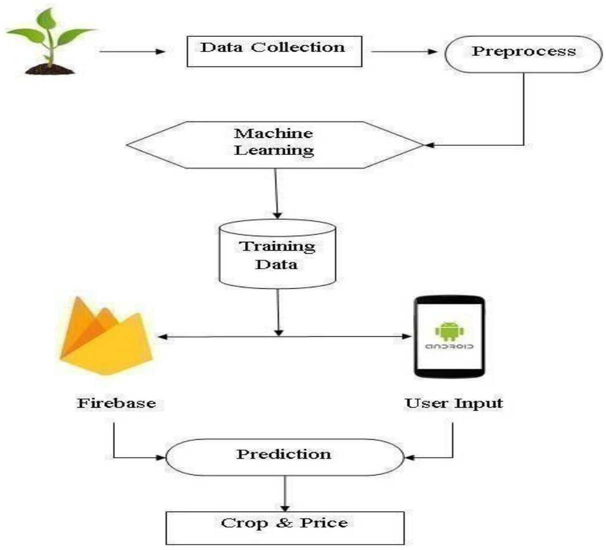
3. Objective

1. To use computer vision to detect fruit size, shape, color and growth stage
2. To analyses growth patterns and health of fruits automatically.
3. To use generative AI to predict future fruit growth and yield.
4. To help farmers make better decisions on irrigation, fertilization, and harvesting
5. To reduce manual effort and human error in fruit growth

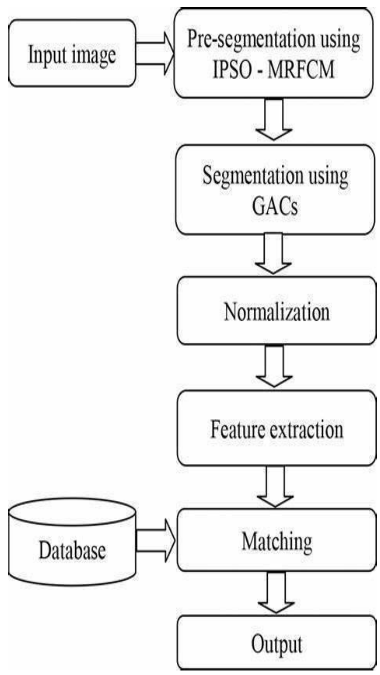
4. Methodology

Image Acquisition: Capture high-resolution images or Environmental Data: Optionally collect related data such as temperature, humidity, and soil conditions to enhance analysis. Image Cleaning: Remove noise, adjust lighting, and standardize image sizes.

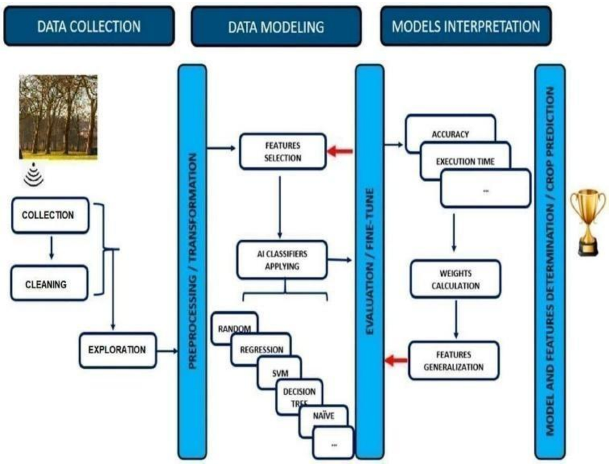
Annotation: Label images with relevant growth stages, fruit counts, size, ripeness levels, or diseases for supervised learning. Data Augmentation: Use generative AI (e.g., GANs) to create synthetic images to expand datasets, improve model robustness, and cover rare growth conditions.



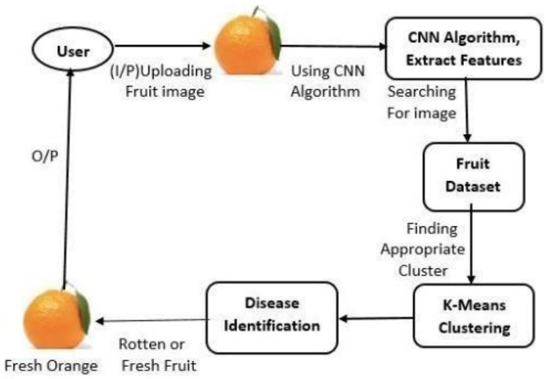
Fig(a). Data Flow Diagram of Proposed System



Fig(b). Different Stages of Proposed System



Fig(c) Activity Diagram for proposed system



Fig(d) Working Model of the System

a. Image Acquisition: High-resolution images (RGB, multispectral, thermal, or 3D depth data) of fruits and their environment are captured using ground-based cameras, drones (UAVs), or sensor rigs.

b. Image Pre-processing: Raw images are processed to remove noise, correct for lighting variations (e.g., shadows, glare), remove backgrounds, and resize images to a standard format.

c. Computer Vision Analysis: Deep learning models (e.g., YOLO, Mask R-CNN) perform the following tasks:

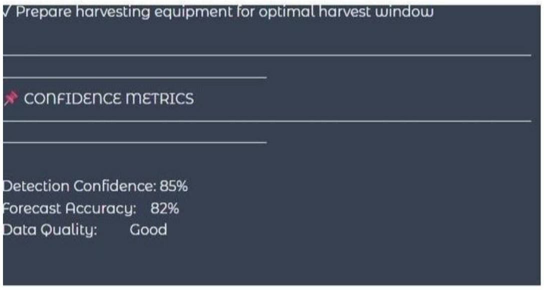
d. Fruit Detection & Counting: Identify and count the number of fruits in the image.

5. Implementation & Results Discussion

Development of modules: Image acquisition, preprocessing, AI models for prediction, user interface.

Integration of computer vision techniques and generative AI models. Use of Python and relevant libraries. Database setup for storing user data and results. Testing modules separately and then integrating. The Generative AI module was implemented using a custom-designed Generative Adversarial Network (GAN) architecture. The generator network comprised deconvolutional layers with batch normalization and Reule activation functions, designed to convert random noise vectors into high- resolution crop images.
The Computer Vision module was implemented using a Convolutional Neural Network (CNN) enhanced with transfer learning. A pre-trained ResNet-50 backbone was fine-tuned using the augmented dataset to extract high-level spatial and spectral features.

During training, the model processed batches of both real and synthetic images along with their corresponding environmental data. Each epoch consisted of forward and backward passes through the generative, vision, and fusion networks



Conclusion

The study successfully developed an automated, AI-driven system for fruit growth monitoring with the following achievements: Accurate fruit growth measurement through computer vision. Efficient disease detection using deep learning. Reliable growth forecasting via generative AI. User-friendly interface facilitating adoption by farmers and experts. Potential to reduce labor and improve crop management decisions. Future work includes expanding to multiple fruit types, Realtime drone integration, and enhanced AI models for more complex disease detection.

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