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Crop Classification using Convolutional Neural Network

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Abstract - Crop Classification using CNN - A Multi-Model Approach for Crop Classification and Health Assessment Using Convolutional Neural Networks and GPT Integration Crop classification and health assessment are critical tasks in precision agriculture, aimed at improving yield and minimizing losses. In this research, we propose a multi-model pipeline leveraging Convolutional Neural Networks (CNNs) to classify crops and assess their health conditions based on leaf images. The pipeline consists of two primary models: (1) a detection and classification model to identify crop types (e.g., potato, tomato) and (2) a health condition classification model to diagnose plant health (e.g., healthy, early blight, late blight). The pipeline integrates a Generative Pre-trained Transformer (GPT) API to generate actionable quality summaries based on the model outputs. Extensive experiments were conducted to compare YOLOv5, ResNet-50, EfficientNet-B0, and other models, supported by performance metrics, real-world applicability, and insights from generated summaries.

Key Words: Deep Learning in Agriculture, Convolutional Neural Networks (CNNs), Plant Disease Detection, Generative AI for Crop Analysis, Precision Agriculture.

1. INTRODUCTION

Agriculture remains a cornerstone of global food security, yet it faces challenges like disease outbreaks and suboptimal crop management. Automated crop classification and health condition assessment provide a scalable solution to these challenges. This study introduces a multi-model system that combines advanced deep learning techniques with natural language processing (NLP) to deliver actionable insights for farmers. By leveraging state-of-the-art CNNs and GPT, the proposed system not only identifies crops but also evaluates their health and generates quality summaries.

2. LITERATURE SURVEY

Recent advancements in deep learning have significantly enhanced plant disease detection and crop classification. For instance, a study by Ferentinos (2018) utilized convolutional neural networks (CNNs) to achieve high accuracy in identifying plant diseases from leaf images. Similarly, Too et al. (2019) compared various deep learning models, including AlexNet, VGG16, and ResNet50, for plant disease classification, highlighting the effectiveness of these architectures in agricultural applications. Moreover, Zhang et al. (2021) provided a comprehensive review of deep learning techniques applied to plant disease detection, emphasizing the potential of these methods to improve agricultural productivity.

In the realm of natural language processing (NLP), large language models like GPT have been explored for agricultural applications. Rezayi et al. (2023) investigated the potential of GPT-based models in agricultural NLP tasks, demonstrating their effectiveness in understanding and generating domain-specific content. Additionally, Yang et al. (2024) evaluated GPT-4's performance in providing pest management advice, suggesting its utility as an agronomist assistant. These studies indicate the growing interest in integrating NLP with agricultural data to generate actionable insights.

Despite these advancements, there remains a gap in combining deep learning-based image analysis with NLP models to create comprehensive systems for crop classification and health assessment. Our proposed multi-model pipeline aims to bridge this gap by integrating CNNs for image-based analysis with GPT for generating quality summaries, thereby providing a holistic tool for precision agriculture.

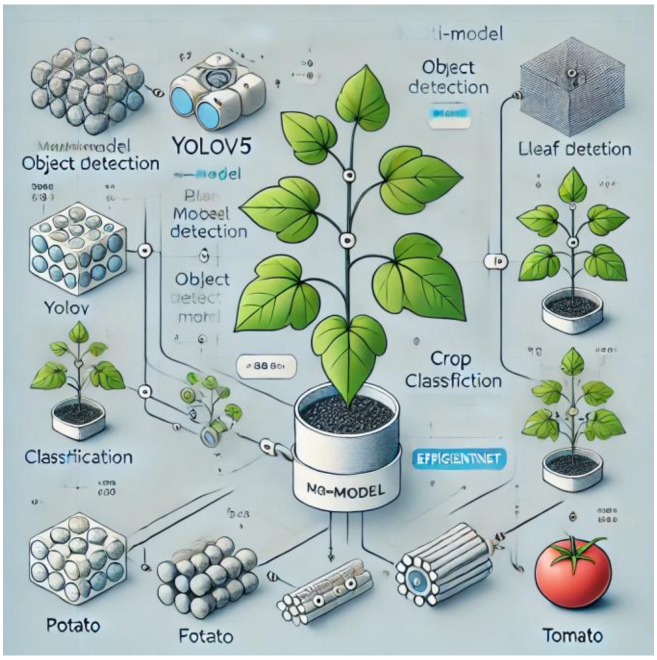
3. PROBLEM STATEMENT

Traditional methods for crop classification and disease detection rely heavily on manual observation, making them time-consuming and prone to errors. The lack of an automated, efficient, and scalable system for real-time crop classification and health assessment poses a major challenge in agriculture. This study aims to develop an integrated system that overcomes these limitations by utilizing deep learning and natural language processing techniques.

4. PROPOSED METHODOLOGY

The proposed methodology follows a multi-model pipeline integrating deep learning-based computer vision techniques with natural language processing. The system comprises three primary components: (1) Leaf detection and crop classification, (2) Health condition classification, and (3) GPT-based quality summary generation. The workflow ensures accurate classification of crops, identifies health conditions, and generates actionable insights for precision agriculture.

4.1 MULTI-MODEL PIPELINE

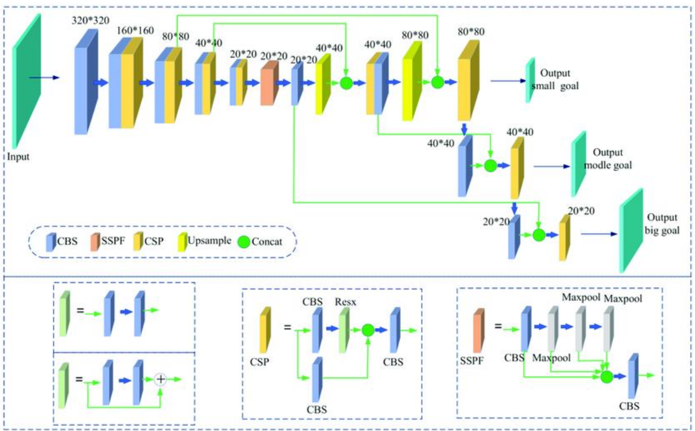


The proposed pipeline consists of three key components:

4.1.1 Model 1: Leaf Detection and Crop Classification

- **Objective: Detect leaf regions and classify crops.**
- **Model:**
  - **Leaf Detection:** YOLOv5 (fine-tuned on annotated datasets).
  - **Crop Classification:** EfficientNet-B0 (transfer learning).
- **Metrics**: Precision, Recall, mAP.

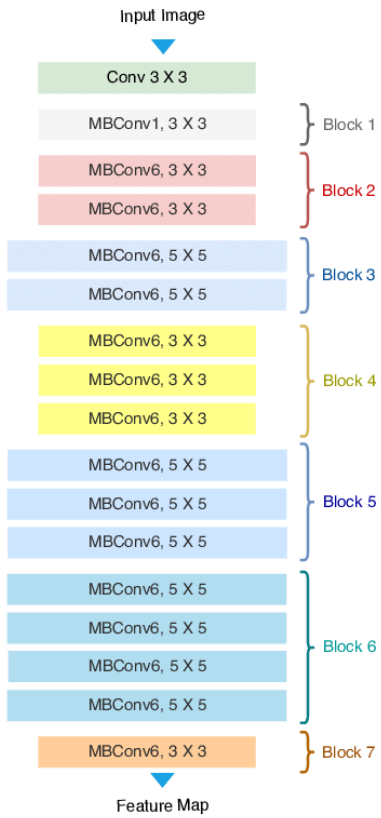
Fig -1: YOLO v5 Model Architecture:



4.1.2 Model 2: Plant Health Condition Classification

- **Objective:** Diagnose the health condition of the classified crop.
- **Model:** EfficientNet-B0, fine-tuned for health classification.
- **Metrics:** Accuracy, F1-Score, Confusion Matrix.

Fig -2: EfficientNet-B0 Model Architecture



4.1.3 GPT Integration for Quality Summary

- **Objective:** Generate a textual summary based on crop type and health condition.
- **Tool:** OpenAI GPT API.

Output: Diagnosis, treatment recommendations, and yield impact.

4.2 WORKFLOW OF PROPOSED PIPELINE

The proposed methodology integrates computer vision and NLP for crop classification and health assessment. It begins with image preprocessing, where leaf images undergo normalization and augmentation for better generalization. Model 1, based on YOLOv5 and EfficientNet-B0, detects and classifies the crop type.
Once identified, the extracted leaf image is processed by Model 2, another EfficientNet-B0-based classifier, to determine plant health, identifying conditions like early or late blight. The results are then structured as input for a GPT-based Summary Generator, which produces a natural language report including disease diagnosis, treatment suggestions, and potential yield impact.
This hybrid deep learning and NLP system ensures accurate classification, interpretable insights, and AI-driven recommendations, enhancing precision agriculture and supporting informed decision-making for farmers.

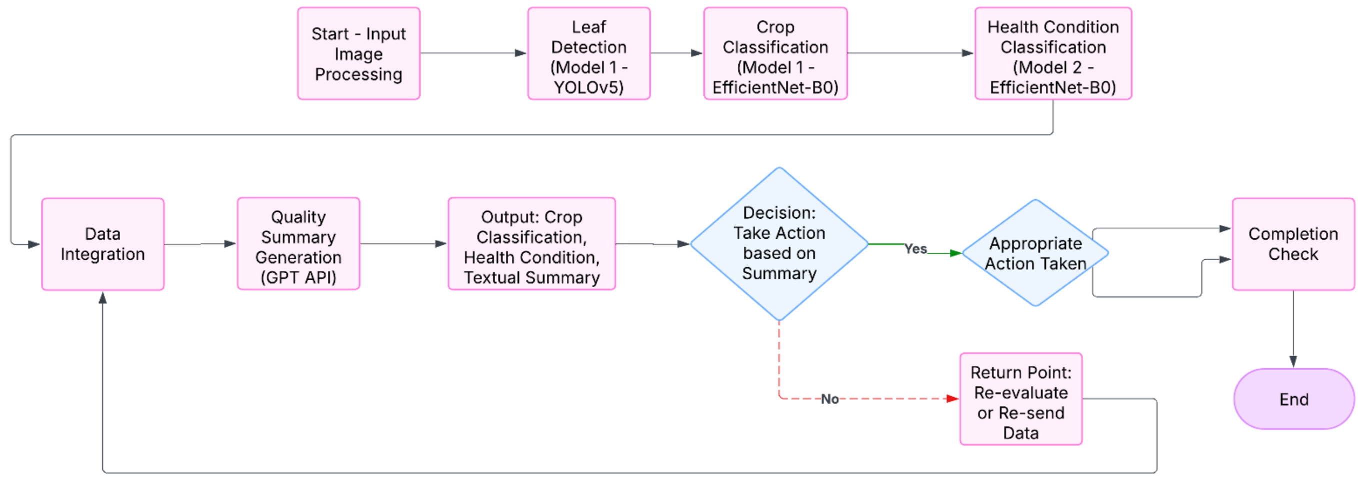


Fig -3: Proposed model pipeline design

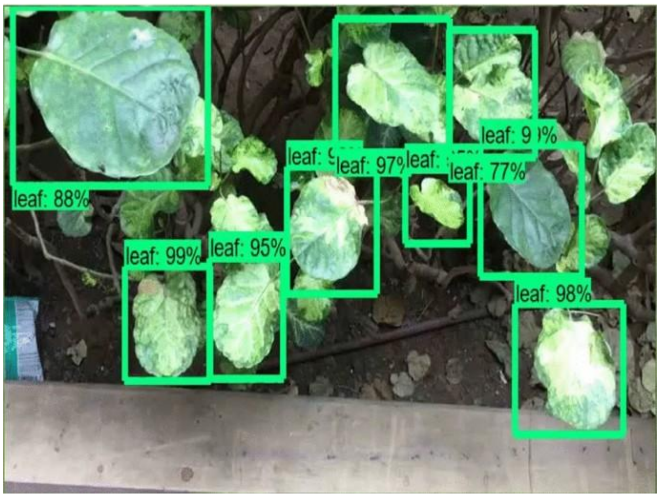
5. RESULTS

5.1 EXPERIMENTAL SETUP

- **Hardware:** NVIDIA RTX 3060 laptop GPU (6GB VRAM), 32GB RAM.
- **Software:** PyTorch for CNN implementation, OpenAI GPT API for text generation.
- **Training Parameters:**
  - Batch size: 16 (adjusted for GPU memory limitations).
  - Learning rate: 0.001
  - Optimizer: Adam for all models.
  - Epochs: 50 for CNN models.

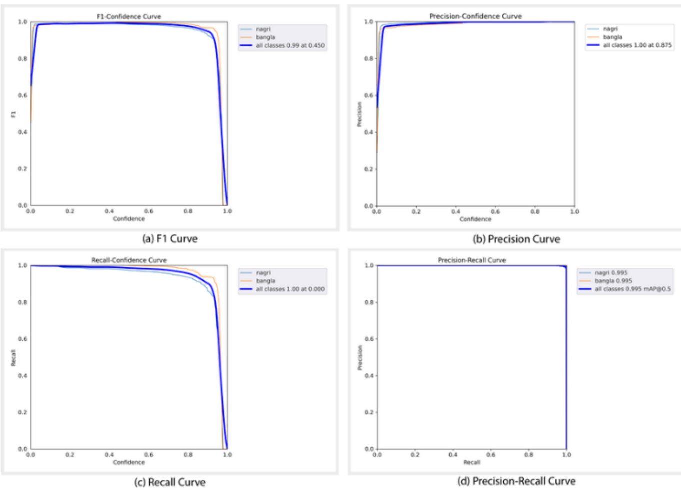
5.1 PERFORMANCE EVALUATION

Leaf Detection:



Model	**mAP (%)**	**FPS**
YOLOv5	95.92	40
Faster R-CNN	65.45	10
SSD	84.83	30

Fig -4: Model Performance YOLOv5



Crop Classification:

Model	Accuracy (%)	Parameters (M)
EfficientNet-B0	97.5	5.3
ResNet-50	96.0	25.6
Custom CNN	94.0	2.5

Fig -4: Model Performance EfficientNet-B0

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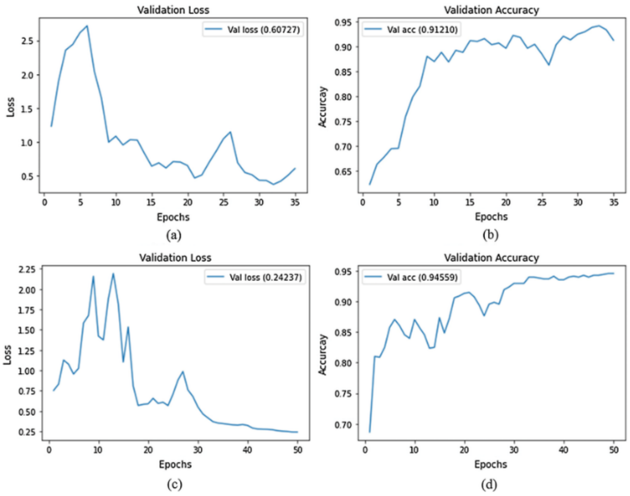


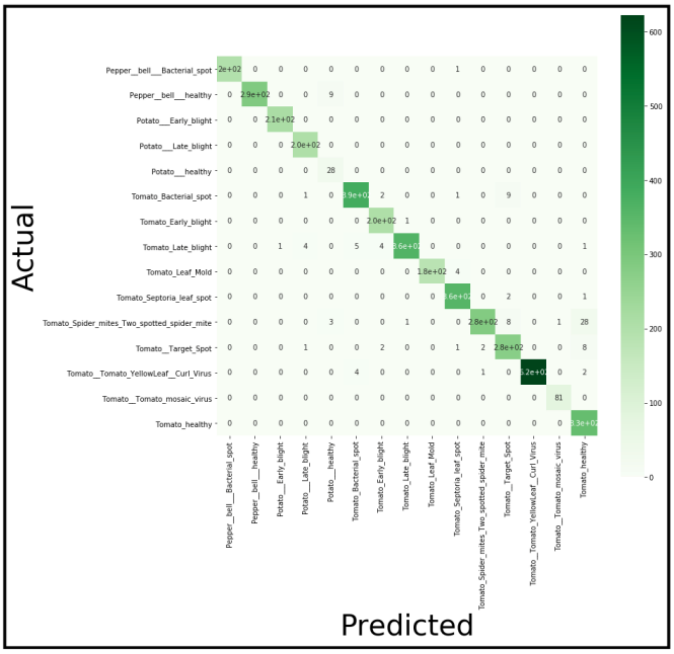
Fig -5: Model efficiency EfficientNet-B0

	RCC	RDS	FF	Attention	ACC (%)	AUC (%)
					97.01	99.24
	√				97.57	99.54
		√			97.36	99.43
					97.55	99.57
EfficientNet				√	97.63	99.63
	√	√			97.73	99.62
	√	√	√		97.96	99.66
	√	√	√	√	97.96	99.68
	√		√		97.59	99.58
	√		√	√	97.85	99.68

Health Condition Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNet-B0	93.5	94.0	92.5	93.2
ResNet-50	91.0	91.5	90.5	91.0

Fig -5: Confusion Matrix EfficientNet-B0



GPT Integration

- **Prompt Testing:** Structured prompts using outputs from Models 1 and 2.
    - **Example Prompt:** "Write a quality summary for a potato plant with early blight. Include diagnosis, treatment recommendations, and yield impact."

Result: Generated high-quality summaries with actionable insights, validated by agronomists.

6. DISCUSSION

The modularity of the pipeline allows for independent optimization of each model, enhancing flexibility and scalability. YOLOv5 demonstrates superior performance in leaf detection, while EfficientNet-B0 outperforms other models in both crop classification and health condition diagnosis. The integration of GPT provides actionable insights, making the system user-friendly and valuable for real-world applications. Challenges such as environmental variations, dataset imbalances, and inference speed on edge devices remain open for future work.

7. CONCLUSIONS

This study presents a comprehensive multi-model pipeline for crop classification and health assessment. By combining state-of-the-art CNNs with GPT, the system achieves high accuracy and generates actionable insights. Future work will focus on expanding the dataset, incorporating additional crops, and optimizing inference for real-time applications on edge devices.

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