Agrobot for Disease Detection and Pesticide Spraying in Tomato Grow Bag Cultivation

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Outline

Introduction

- Agriculture remains the backbone of India, however traditional farming methods have not kept pace with modern technological advancements.
- Traditional farming methods require extensive manual labor, increasing cost and leading to the risk of human error.

Why robots in agriculture?

- In agriculture, the opportunities for robot-enhanced productivity are immense and the robots are appearing on farms in various guises and in increasing numbers.
- Robots in agriculture are revolutionizing traditional farming practices by enabling precision and efficiency in every step of the process.

Background Information/Related Works

Challenge	Impact	How Robots Help	Data/Statistics
Labor Shortage	Fewer workers due to migration & aging.	Robots reduce reliance on human labor.	Labor availability dropped **20-40%** (FAO).
Precision	Inconsistent quality & crop loss.	AI & vision systems improve accuracy.	Yield improves **20-30%** (IEEE).
Time Efficiency	Manual harvesting is slow.	Robots work **3-5x faster**.	Robots harvest **25 acres/day** vs. **1 acre manually**.
High Costs	Rising wages increase expenses.	Long-term savings despite high setup.	Labor costs **50-70%** of expenses.
Safety	Risk of injuries & harsh conditions.	Robots handle tough tasks safely.	Injury rates drop **30-50%** (OSHA).
Sustainability	Overuse of resources like water & pesticides.	Robots optimize resource use.	Pesticide use drops **90%**, water **30-50%**.

Background Information/Related Works

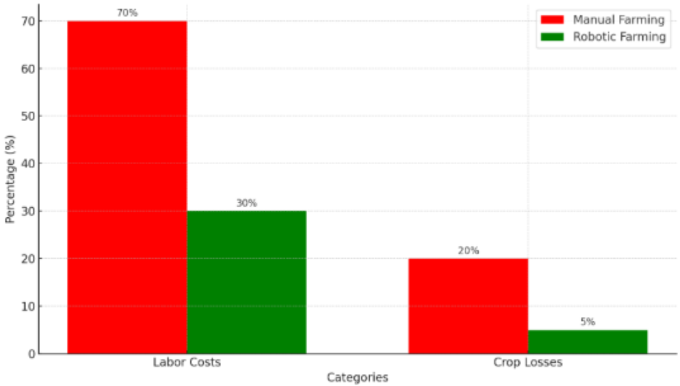


Figure: Labour Costs and Crop Losses: Manual vs Robotic Farming

Background Information/Related Works

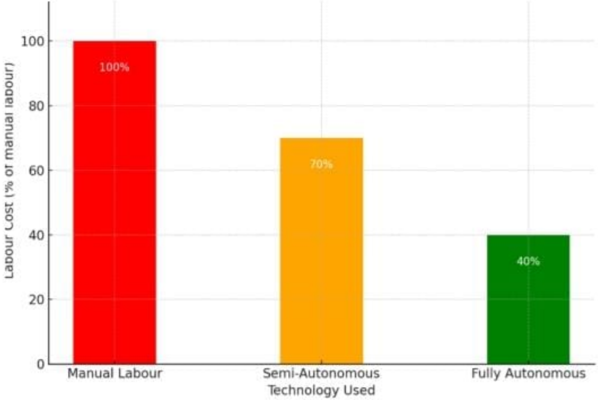
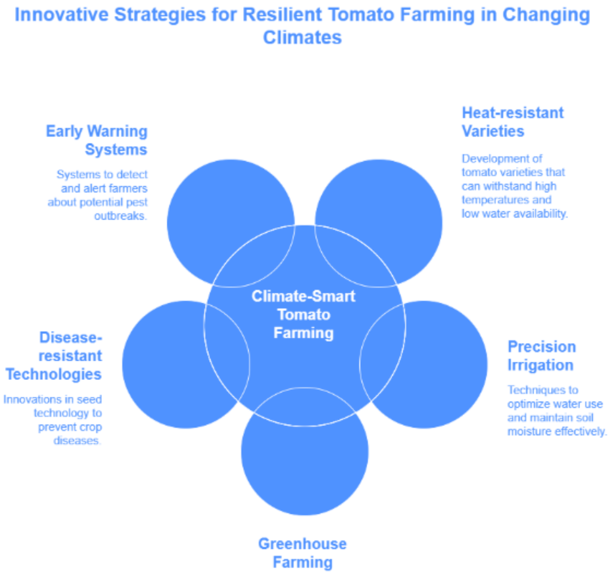


Figure: Labour costs in agriculture with different levels of automation

Table 2: Benefits of Robots in Tomato Cultivation

Aspect	Manual Method	Robot-Assisted Method	Improvement (%)
Harvesting Time	1.5 hours to harvest 100 plants	0.5 hours to harvest 100 plants	**200% faster**
Labor Cost per Acre	$1,200	$400	**67% cost reduction**
Yield Quality	70% market-grade tomatoes	90% market-grade tomatoes	**28% increase in quality**
Pesticide Use	20 liters per acre	12 liters per acre	**40% reduction**
Food Waste Reduction	15% post-harvest waste	5% post-harvest waste	**66% less waste**
Operational Hours	Limited to 8-10 hours/day	24/7 operation possible	**3x more operational hours**

Innovative Strategies



Disease Detection in Tomato and Pesticide Sparying

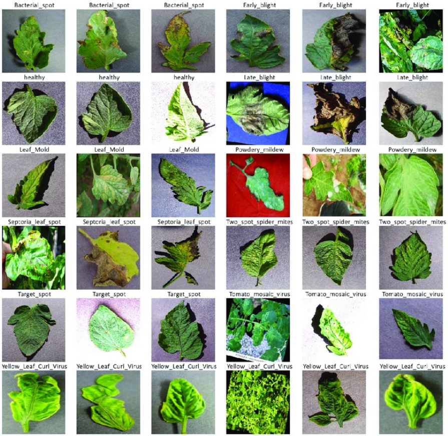


Figure: Disease Detection in Tomato and Pesticide Sparying

Literature Survey

Multi-Purpose Agricultural Robot

[1]

- Design and development of a multi-purpose agricultural robot capable of automating key farming tasks.
- Merits:Cost-effectiveness, environmental sustainability, and increased productivity.
- Limitations : shallow ploughing depth and dependence on adequate sunlight for optimal performance.

Literature Survey

Smart Farming Robot for Detecting Environmental Conditions in a Greenhouse

[2]

- Design and implementation of a smart farming robot that monitors environmental conditions within a greenhouse to optimize plant growth.
- Merits – Reduces the need for manual monitoring, improving greenhouse management efficiency.
- Challenges – Unsupervised learning requires large datasets to function effectively, which may be a challenge in early-stage adoption.

Literature Survey

Autonomous tomato harvesting robotic system in greenhouses: deep learning classification

[3].

- Based on Convolutional Neural Networks (CNNs) to accurately identify and differentiate tomatoes from other objects.
- Merits - Enhances harvesting efficiency and reduces reliance on manual labor in greenhouse farming.
- Challenges – The model was trained on Limited Dataset which is insufficient for robust deep learning performance.

Summary of Literature Survey

- Precision: Sensor-based deep learning ensures accurate crop classification and control.
- Existing Challenges: Data limitations, ploughing depth, and sunlight dependency affect performance.
- Future Potential: AI advancements, larger datasets, and adaptive hardware will enhance efficiency.

Research Gap

1	Lack of Focus on **Disease Detection**
2	Focused on large scale not suited for small scale grow bag farming.
3	Research is limited to quality of Datasets available.
4	Most products are not crop specific.
5	Cost Constraint

Objectives

1. Disease Detection for 10 Classes with CNNs

The system detects various diseases in tomato plants using CNN-based classification.

2. Automated Pesticide Spraying

Automatically sprays pesticides based on disease detection to minimize human intervention.

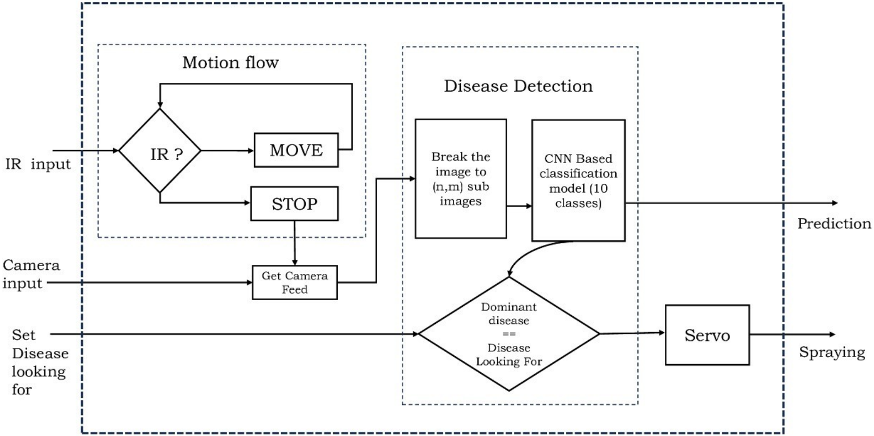
3. Autonomous Navigation

The robot autonomously navigates through the cultivation area for effective task execution.

Proposed Work

- **The system enables autonomous operation using machine learning and real-time processing, allowing the robot to perform disease detection, and precise pesticide application without human intervention.**
- **A CNN based deep learning model to classify and detect diseases from images**
- **Motors for navigation ,IR sensor for growbag detection and dc pump to pump pesticide , all controlled by Raspberry Pi.**

System Block Diagram



Deep Learning Workflow

Class	Train Images	Validation Images	Test Images
Bacterial_spot	1,699	225	200
Early_blight	1,920	280	200
Healthy	1,936	281	200
Late_blight	1,851	263	200
Leaf_Mold	1,902	270	200
Mosaic_virus	1,800	248	200
Septoria_leaf_spot	1,745	236	200
Target_Spot	1,837	257	200
Two-spotted_spider_mite	1,741	235	200
Yellow_Leaf_Curl_Virus	1,961	290	200

- This table represents a dataset of images categorized into different classes related to plant diseases and health conditions.

Deep Learning Workflow

Layer (Type)	Output Shape	Details
Input Layer	(None,224, 224, 3)	RGB image input
Conv2D	(None,222, 222, 32)	32 filters, (3×3) kernel
Batch Normalization	(None,222, 222, 32)	Normalizes activations
Conv2D	(None,220, 220, 32)	32 filters, (3×3) kernel
Batch Normalization	(None,220, 220, 32)	Normalizes activations
MaxPooling2D	(None,110, 110, 32)	(2×2) pooling
Conv2D	(None,108, 108, 64)	64 filters, (3×3) kernel
Batch Normalization	(None,108, 108, 64)	Normalizes activations
Conv2D	(None,106, 106, 64)	64 filters, (3×3) kernel
Batch Normalization	(None,106, 106, 64)	Normalizes activations
MaxPooling2D	(None,53, 53, 64)	(2×2) pooling
Conv2D	(None,51, 51, 128)	128 filters, (3×3) kernel
Batch Normalization	(None,51, 51, 128)	Normalizes activations
Conv2D	(None,49, 49, 128)	128 filters, (3×3) kernel
Batch Normalization	(None,49, 49, 128)	Normalizes activations
MaxPooling2D	(None,24, 24, 128)	(2×2) pooling
Global Average Pooling	(None,128)	Reduces feature maps
Dropout	(None,128)	Regularization
Dense (Fully Connected)	(None,256)	Fully connected layer
Dropout	(None,256)	Regularization
Dense (Output Layer)	(None,10)	Softmax activation (10 classes)

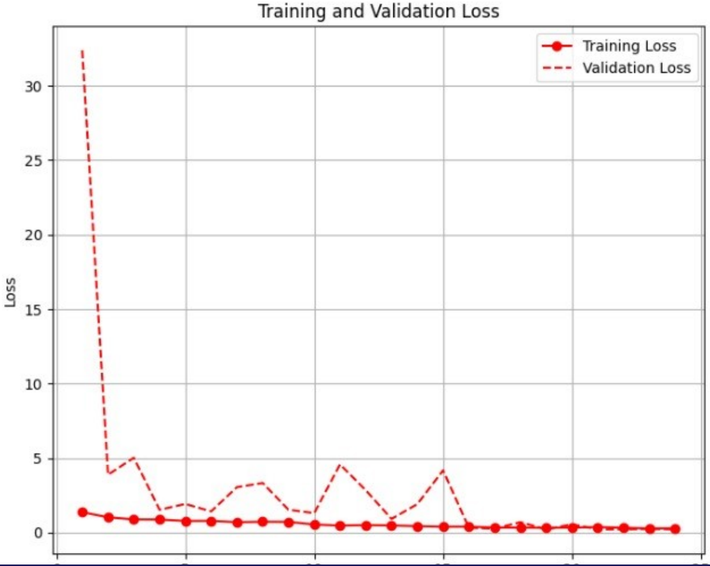
- This CNN (Convolutional Neural Network) model follows a deep learning architecture designed for image classification tasks.

Deep Learning Workflow

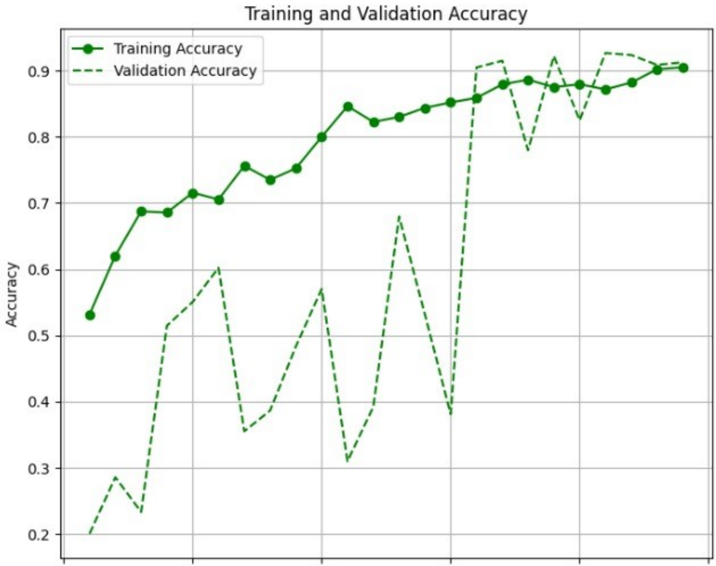
Hyperparameters used in training

- Epochs: 50
- Learning Rate: 0.01
- Optimizer: Adam
- Loss Function: Categorical Crossentropy
- Batch Size: 32
- Input Shape: (224, 224)

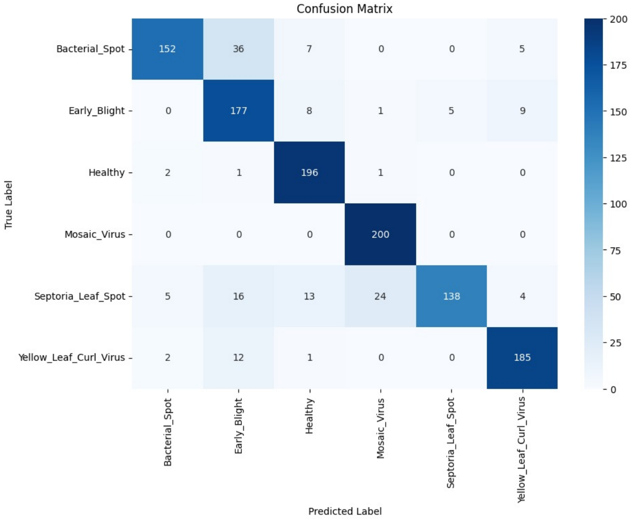
Training Progress Graphs



Training Progress Graphs



Confusion Matrix



- This confusion matrix visualizes the performance of a classification model on test data.

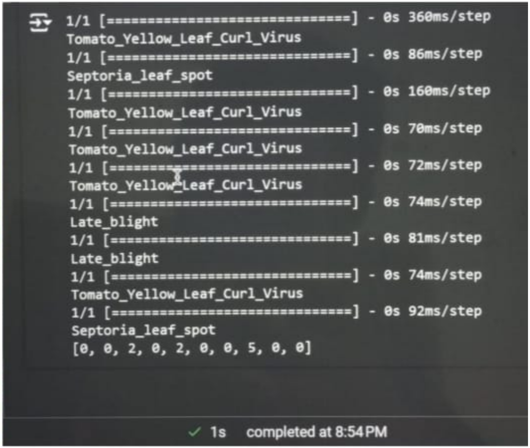


Figure: Disease Detection using ML

Initial CAD Design

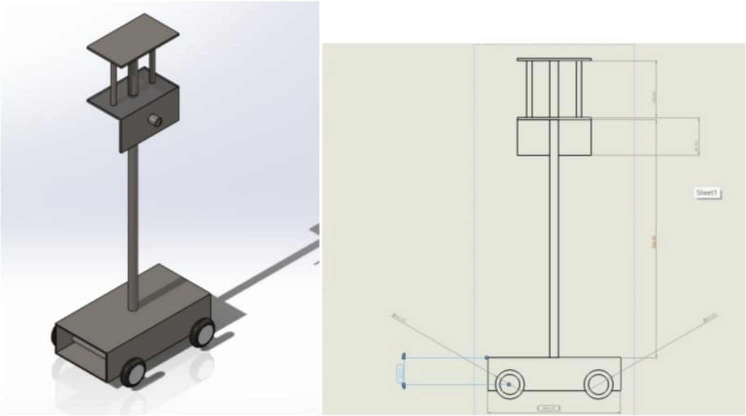


Figure: Initial CAD Design

Results

- **Successful Disease Detection:** Achieved 91% accuracy, 92% precision, and 90% recall using a CNN-based model.
- **Autonomous Spraying:** Pesticides applied precisely based on disease detection, reducing manual effort.
- **Fully Autonomous Operation:** Navigation, detection, and spraying are completed without human intervention.

Result image

Result image

References

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