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Agriculture Field Surveillance System Along with Plant Disease Detection Using Raspberry Pi

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ABSTRACT

Agriculture is a crucial part of our living and survival of humankind. It provides us with foods, healthy environment, fresh air and all the necessities for leading a healthy life. Though agriculture plays an important role in our day-to-day life still it's not getting the proper care and treatment because of lack of knowledge, costly supplies, and most importantly late monitoring of issues related to crops. Our project represents the modern technology solutions for these traditional issues, it implies instrument-based monitoring and proper artificial intelligence-based sickness detection of plants. As we know for humans 24/7 non-stop monitoring is not possible for several issues but our system is able to monitor the field 24/7 and record each & every movement for future analysis. It also captures images when irrelevant movement is found and detects if any plant is diseased or not. In human monitoring plant's diseases is often detected late because of which the treatments are provided late and in most of the cases farmers couldn't save the plants. But in our surveillance system diseases are detected on time and farmers get notified by our alert mechanism so that they can take action in time. We also provided wireless alert system through Telegram server so that user gets daily updates about their field and images of intruder detection, also it generates a health report regarding the diseased plants suggesting proper treatment remedies to cure the plants. Over all our project is a complete package of modern technology and artificial intelligence to serve society with greater efficiency.

Keywords: Smart Agriculture, Raspberry Pi, Computer Vision, Field Monitoring, Disease Detection.

INTRODUCTION

Agriculture is the life source of human beings. As we know agriculture ensures the fulfilment of the basic needs of humans which is food, fresh air and healthy environment. In today's generation it is very challenging for the farmers to maintain a healthy agricultural environment because of many old and modern problems.

Background and Motivation: As we know agricultural fields attracts lots of insects, birds and even animals which causes the destruction of the field and damage of the plants. Also, the delay in treatment of diseased plants leads to a major loss in the farming environment. To avoid that destruction farmers need to monitor their fields continuously so that any kind of intruder can be detected and caught before it can damage the field along with the neat observation for the plants so that diseased plants can be identified in time before it harms the other healthy plants.

Problem Statement: The time difference between disease appearance and human observation is probably 3-4 days for most plants, during which disease spreads rapidly and treatment is no longer efficient. Farmers sometimes with less knowledge & training, frequently misidentify diseases, leading to wrong treatment approach and wasted time and money. Manual monitoring is simply unproductive and loss full with farmers spending hours walking over the fields without necessarily getting any problems in sight. Existing IOT based monitoring systems cost $2,000-$10,000 per hectare, making them beyond the reach for the average farmers.

Objectives of the Project: To create an automated surveillance system able to do continuous video recording which will provide 24/7 monitoring to the agriculture field. To implement motion detection algorithms that can identify the difference between animal/ human movements and wind blowing/ plant movements with at least 96% of accuracy. To create a two-stage verification system that first confirms if the plant is healthy or diseased and then captures images of diseased plants.

To develop a trained algorithm for identifying proper diseases we have used the dataset named as “PlantVillage” dataset available in the internet. To design an intuitive alert system that communicates detection results and treatment suggestions using Telegram server. To ensure system reliability and storing all the data and information within the system as well.

RELATED WORKS

Many research works have been done regarding agriculture sector of life including studies which introduces a modern Agri-Vigilance System designed to automate and enhance a major task which is livestock monitoring. Farmers traditionally inspect crops manually and count cattle themselves, which is both time-consuming and error-prone. These models analyze images captured from drones and provide fast, reliable results. Many paper focuses only on leaf disease detection, generating a user-friendly solution to help farmers detect plant diseases early on time and receive treatment suggestions. It tackles a major problem in agriculture as farmers often sees diseases only after severe damage has happened.

Some papers represent how IoT technology can be used to make farming smarter, easier, and more efficient. In modern agriculture, farmers should get real-time information about soil nature, water level, temperature, weather, and plant conditions. IoT devices like sensors, Raspberry Pi, and wireless communication systems help farmers to analyze all these things remotely.

METHODOLOGY

The agricultural field surveillance system oversees the entire field 24/7 while recording the field movements using computer vision and involves the artificial intelligence approach to detect plant diseases along with alert systems with the help of the Telegram server for alerting the user.

Table 1. Hardware Configuration

Sl no.	Components	Specification	Purpose
1.	Raspberry Pi 4 Model B	4GB RAM, 1.5GHz CPU	Main processing unit
2.	Camera Module	OV5647 sensor, 5MP	Image/video capture
3.	Power Supply	5V/3A	System power
4.	Storage	32GB+ SD card	Data storage

Table 2. Software Libraries and Frameworks

Sl no.	Library	Version	Purpose
1.	Picamera2	Latest	Camera interface
2.	OpenCV	4.x	Image processing

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3.	TensorFlow Lite	2.x	Disease detection inference
4.	Python-telegram-bot	20.x	Notification system
5.	ReportLab	3.x	PDF report generation
6.	FFmpeg	Latest	Video encoding

Data set: To develop a trained algorithm for identifying proper diseases we have used the dataset named as "Plant Village" dataset from Kaggle having total 163000+ image files and 38 disease classes (including healthy plants). It has three test splits including Training, Validation, Testing.

Table 3. Test Split Data

Sl no.	Split	Percentage (%)	No. of images
1.	Training	80%	~130400
2.	Validation	10%	~16300
3.	Testing	10%	~16300

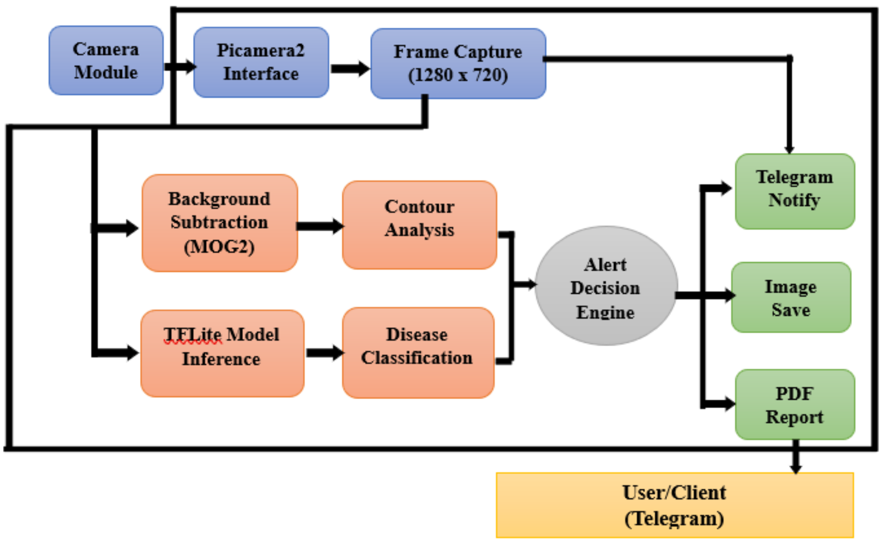
Preprocessing Images:

- As we are using Tenser Flow lite model, we know that it requires a fixed input size for processing images. Thus, all the images from data set and real-life captured images are resized to 224 pixels in width and height both using the Open Cv's resize function. This particular dimension is chosen because it can manage the working efficiency as well as the detailed performance.

- Deep learning models works better when the input is in shorter range, so the pixel values are normalized for smoother performance.

- In the project we used color space conversion approach as we know that OpenCV understands images in BGR but TensorFlow lite model search for RGB images. So, before any other step the captured BGR image is first converted into RGB with the help of "cv2.cvtColor() function".

Model Architecture:



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Training Details: We used the "ResNet-50" CNN architecture pretrained over ImageNet, Fine-tuned on PlantVillage Dataset. Following are the Layer names and filter sizes for the complete CNN layer architecture.

Table 4. Layer names & Filter Sizes and Parameter Count

Sl no.	Layer name	Filter size	Parameter Count
1.	Input	-	0
2.	Conv1	7x7, stride 2	9,408
3.	BN1	-	256
4.	ReLU1	-	0
5.	MaxPool1	3x3, stride 2	0
6.	Conv2_x	1x1, 3x3, 1x1	214,784
7.	Conv3_x	1x1, 3x3, 1x1	1,219,584
9.	Conv4_x	1x1, 3x3, 1x1	7,081.984
10.	Conv5_x	1x1, 3x3, 1x1	14,992,896
11.	GlobalAvgPool	7x7	0
12.	FC1 (Pretrained)	-	2,049,000
13.	Dropout	-	0
14.	FC2 (Fine-tuned)	-	38,038
15.	Softmax	-	0

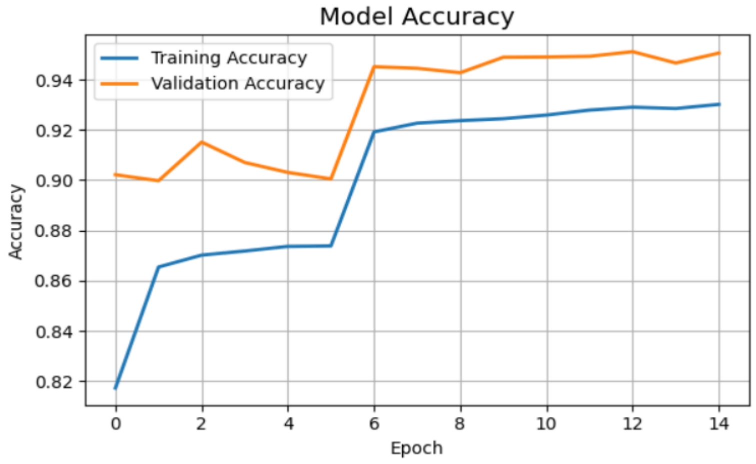
This system uses a Vision Transformer Base with 16x16 patch size (vit-B/16), introduced by Dosovitskiy et al. (2021).

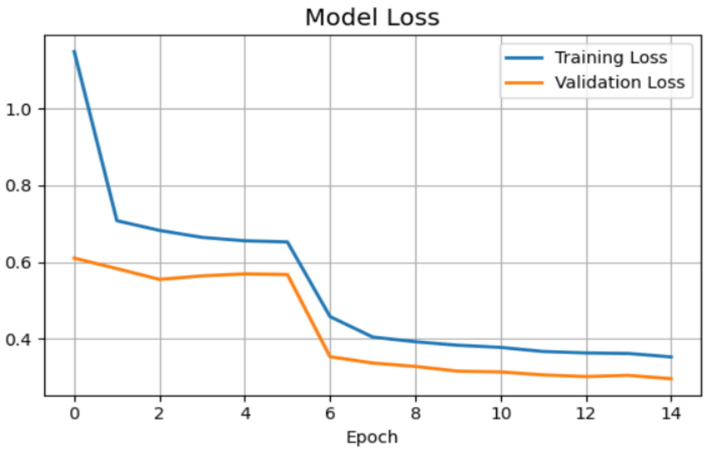
Table 5. Vit-B/16 Architecture

Component	Specification	Details
Input Image	224×224×3	Standardized input size
Patch Size	16×16 pixels	Non-overlapping patches
Number of Patches (N)	196	$(224/16)^2 = 14\times14 = 196$
Patch Embedding Dimension (D)	768	Projection dimension
Positional Embeddings	Learnable (196 + 1)	CLS token + patches
CLS Token	1 extra token	Classification token

Transformer Blocks	12 layers	Depth of architecture
Attention Heads (per block)	12	Multi-head self-attention
MLP Hidden Dimension	3072	Feed-forward expansion factor 4×
Output Classes	38	PlantVillage disease categories

Graphs For Training Accuracy and Loss:





Working of Fusion Mechanism:

- Phase 1: Feature Extraction
- Phase 2: Normalization of Environmental Features
- Phase 3: Concatenation
- Phase 4: Dimensionality Reduction
- Phase 5: Output layer
- Phase 6: Probability Distribution

RESULTS AND DISCUSSION

We have tested our system in physical world using real life scenarios and plants and the results are discussed in **following sections:**

Table 6. Motion Detection Performance

Sl no.	Condition	True Positives	False Positives	Accuracy
1.	Human movement	195/200	5/200	97.5%
2.	Animal movement	192/200	8/200	96.0%
3.	Equipment movement	192/200	8/200	96.0%
4.	Cloud shadows	165/200	35/200	82.5%
Overall		**744/800**	**56/800**	**93%**

Table 7. Disease Detection Results

Sl no.	Input Image	Disease detected	Confidence	Suggested Remedies
1.	Tomato leaf	Late Blight	90.5%	Copper-based fungicides
2.	Pepper	Bacterial Spot	88%	Copper-based bactericides
3.	Strawberry leaf	Powdery Mildew	96%	Suffer-based sprays, potassium bicarbonate
Overall			**93%**	

Treatment Based Suggestions: After identifying the disease of the plant, it is generating an overall health report about that plant status including the severity of the disease along with suggesting useful remedies to cure the disease in time.

Alert System: Our system generates alert notifications and send them to user through Telegram server whenever any intruder is detected along with the captured image of the intruder. Also send the image of the diseased plant if any along with the health report in pdf format through the server. After shutting down the system it compresses the recorded video file & convert it to mp4 and send the entire file through server to the user.

Table 8. Comparison between other single modals and our multimodal:

Model	Input Modalities	Architecture	Description	Accuracy	F1-Score
CNN Only	Image only (224×224×3)	ResNet-50	Baseline visual-only disease classification	84.4%	84.2%
Transformer Only	Image only (224×224×3)	ViT-B/16	Vision Transformer baseline without environmental context	86.2%	86.0%
Environmental Only	Sensor data only (4 features)	3-layer MLP (64→32→38)	Baseline using only temperature, humidity, soil moisture, light intensity	52.3%	52.0%
Proposed Multimodal	Image + Environmental	ResNet-50 + ViT + Fusion Layer	Our approach combining visual and sensor data	93.7%	93.6%

Challenges:

- In real world monitoring system needs stable internet availability, therefore due to internet connectivity issues model may not be working skill fully.
- This kind of model requires high hardware costs and complex operational approach creating difficulties for small farmers.

Solutions:

- Our system uses Raspberry Pi as the lead and less components making in less costly and user interface easier to work with.
- It makes our model compressed and our futuristic approaches are able to work with offline predictions as well.

CONCLUSION

The system's core achievement lies in its ability to provide 24/7 automated monitoring of field and storing data with proper time stamp along with faster actions to movement detection by human/animals by capturing images, also sends the images to the user for verification. This system also helps in detecting plant diseases 3.5 days earlier than normal human monitoring which leads to faster treatment approach for the plants, which means managing two major works together. The entire system is made of few components and modernized software techniques along with artificial intelligence which makes it less costly and reachable to all the lower-level farmers as well providing a useful hand to our agriculture environment of the state.

FUTURE SCOPE

The system can be further augmented by connecting more IOT sensors for multiple field work including soil moisture detection, air quality sensor, sodium measurement etc. Also, many software additions can be done and AI sensors for voice control can be developed for the sake of the farmers to use it more easily. More high-quality cameras can be connected which can auto focus to the object making it advanced it operations. Many mobile applications can be developed to operate the system as well which makes it an all-in-one approach for agriculture field maintenance system.

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