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A PROJECT REPORT ON

" AI-Based Plant Disease Classification System "

submitted to the Savitribai Phule Pune University

In partial fulfillment of the requirement for the award of the Degree of

BACHELOR OF ENGINEERING

ELECTRONICS & TELECOMMUNICATION ENGINEERIN By

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CERTIFICATE

This is to certify

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have satisfactorily completed project part-I and presented a report on the topic titled **" AI-Based Plant Disease Classification System "** at Dr D. Y. PATIL SCHOOL OF ENGINEERING in partial fulfillment of requirement of Savitribai Phule Pune University, Pune, for the degree of BE (Electronics and Telecommunication Engineering) in semester VIl during academic year 2023-2024.

Guide	Coordinator	H.O. D	Principal
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Name:

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Name:

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ABSTRACT

The "AI-Based Plant Disease Classification System" is a cutting-edge tool in the field of agriculture that uses deep learning and artificial intelligence to automatically identify and categories plant diseases. This technology intends to transform agricultural practices, improve crop output, and encourage sustainable farming for a better agricultural future by offering timely insights about crop health.

CHAPTER 01

INTRODUCTION

The "AI-Based Plant Disease Classification System" is a cutting-edge tool in the field of agriculture that uses deep learning and artificial intelligence to automatically identify and categorise plant diseases. This technology intends to transform agricultural practices, improve crop output, and encourage sustainable farming for a better agricultural future by offering timely insights about crop health.

The combination of artificial intelligence (AI) and deep learning techniques represents a viable approach to tackling these challenges. This system uses cutting-edge machine learning algorithms to automatically detect and classify plant illnesses, allowing farmers to quickly identify and reduce possible crop dangers. By analysing photos of unhealthy plants, the technology can accurately diagnose the problem, allowing for more targeted therapy.

The primary objective of this project is to empower farmers with a reliable tool for early disease detection, thereby enhancing crop management practices and optimizing agricultural productivity. Through the utilization of cutting-edge technology, this system aims to revolutionize traditional farming methods, foster sustainable agricultural practices, and contribute to global efforts aimed at ensuring food security for future generations.

This introduction clarifies the significance of early disease identification and lays the groundwork for a thorough examination of the disease classes and their descriptions. The table below show the classes which model can identify with their descriptions.

Disease Classes Table:

Sr. No.	Plant	Disease	Reason	Treatment
1	Apple	Apple scab	Fungal disease affecting apple trees, characterized by dark lesions on leaves and fruit.	Fungicides such as Captan, Mancozeb, or Thiophanate-methyl.
2		Black rot	Fungal disease causing dark, spreading lesions on apple fruit, leading to decay.	Fungicides such as Captan, Myclobutanil, or Thiophanate-methyl.
3		Cedar apple rust	Fungal infection common in apple and cedar trees, causing orange spots on leaves.	Fungicides such as Captan, Myclobutanil, or Thiophanate-methyl.
4		Healthy	Represents healthy apple plants without any disease symptoms.	-
5	Background (No Leaf)	Without leaves	Background image with no leaves or plants.	-
6	Blueberry	Healthy	Represents healthy blueberry plants without any disease symptoms.	-
7	Cherry	Healthy	Represents healthy cherry plants without any disease symptoms.	-
8		Powdery mildew	Fungal disease affecting cherry trees, characterized by white powdery growth on	Fungicides such as Myclobutanil, Propiconazole,

			leaves.	or Sulphur.
9	Corn	Cercospora leaf spot Gray leaf spot	Fungal disease causing grayish lesions on corn leaves, impacting crop yield.	Fungicides such as Chlorothalonil, Azoxystrobin, or Propiconazole.
10		Common rust	Fungal infection causing reddish-brown pustules on corn leaves, affecting yield.	Fungicides such as Azoxystrobin, Propiconazole, or Thiophanate-methyl.
11		Healthy	Represents healthy corn plants without any disease symptoms.	-
12		Northern Leaf Blight	Fungal disease causing large tan lesions on corn leaves, affecting yield.	Fungicides such as Azoxystrobin, Chlorothalonil, or Propiconazole.
13	Grape	Black rot	Fungal disease causing black lesions on grape leaves and fruit, leading to decay.	Fungicides such as Captan, Myclobutanil, or Thiophanate-methyl.
14		Esca (Black Measles)	Fungal disease causing dark spots on grape leaves and trunk, leading to decline.	Fungicides such as Propiconazole, Thiophanate-methyl, or Trifloxystrobin.
15		Healthy	Represents healthy grape plants without any disease symptoms.	-
16		Leaf blight (Isariopsis Leaf Spot)	Fungal disease causing brown spots on grape leaves, affecting yield.	Fungicides such as Azoxystrobin,

				Chlorothalonil, or Propiconazole.
17	Orange	Haunglongbing (Citrus greening)	Bacterial disease affecting citrus trees, causing yellowing and decline.	There is no cure for the disease, but management strategies involve the use of insecticides to control the insect vector, such as Imidacloprid or Spirotetramat.
18	Peach	Bacterial spot	Bacterial disease causing dark lesions on peach leaves and fruit, impacting quality.	Copper-based bactericides or bacteriophages are commonly used.
19		Healthy	Represents healthy peach plants without any disease symptoms.	-
20	Pepper bell	Bacterial spot	Bacterial disease causing dark lesions on pepper leaves and fruit, impacting yield.	Copper-based bactericides or bacteriophages are commonly used.
21		Healthy	Represents healthy bell pepper plants without any disease symptoms.	-
22	Potato	Early blight	Fungal disease causing dark concentric lesions on potato leaves, affecting yield.	Fungicides such as Chlorothalonil, Mancozeb, or Propiconazole.
23		Healthy	Represents healthy potato plants without	-

			any disease symptoms.	
24		Late blight	Fungal disease causing dark lesions on potato leaves and stems, leading to tuber rot.	Fungicides such as Chlorothalonil, Mancozeb, or Metalaxyl.
25	Raspberry	Healthy	Represents healthy raspberry plants without any disease symptoms.	-
26	Soybean	Healthy	Represents healthy soybean plants without any disease symptoms.	-
27	Squash	Powdery mildew	Fungal disease causing white powdery growth on squash leaves and stems.	Fungicides such as Potassium bicarbonate, Sulfur, or Thiophanate-methyl.
28	Strawberry	Healthy	Represents healthy strawberry plants without any disease symptoms.	-
29		Leaf scorch	Fungal disease causing brown lesions on strawberry leaves, impacting yield.	Fungicides such as Azoxystrobin, Chlorothalonil, or Propiconazole.
30	Tomato	Bacterial spot	Bacterial disease causing dark lesions with yellow halos on tomato leaves and fruit.	Copper-based bactericides or bacteriophages are commonly used.
31		Early blight	Fungal disease causing brown concentric lesions on tomato leaves, affecting yield.	Fungicides such as Chlorothalonil, Mancozeb, or

				Propiconazole.
32		Healthy	Represents healthy tomato plants without any disease symptoms.	-
33		Late blight	Fungal disease causing dark lesions on tomato leaves and fruit, impacting yield.	Fungicides such as Chlorothalonil, Mancozeb, or Metalaxyl.
34		Leaf Mold	Fungal disease causing yellowish lesions on tomato leaves, impacting yield.	Fungicides such as Azoxystrobin, Chlorothalonil, or Propiconazole.
35		Septoria leaf spot	Fungal disease causing small dark spots with light centers on tomato leaves.	Fungicides such as Azoxystrobin, Chlorothalonil, or Propiconazole.
36		Spider mites Two-spotted spider mite	Pest infestation causing stippling and webbing on tomato leaves.	Miticides such as Abamectin, Bifenazate, or Spiromesifen.
37		Target Spot	Fungal disease causing concentric rings on tomato leaves, impacting yield.	Fungicides such as Azoxystrobin, Chlorothalonil, or Propiconazole.
38		Tomato mosaic virus	Viral disease causing mottled patterns on tomato leaves and fruit, impacting yield.	There is no cure for the virus. Management involves controlling vectors and removing

				infected plants to reduce spread.
39		Tomato Yellow Leaf Curl Virus	Viral disease causing yellowing and curling of tomato leaves, impacting yield.	There is no cure for the virus. Management involves controlling vectors and removing infected plants to reduce spread.

CHAPTER 02

LITERATURE REVIEW

2.1 Literature Survey:

Author	Title	Publisher	Techniques Used	Area Of Improvement
Ferentinos, K. P.	Deep learning models for plant disease detection and diagnosis	Computers and Electronics in Agriculture, 145, 311-318	CNNs (Various architectures like VGG, ResNet, Inception)	Comparison of CNN architectures, Transfer learning techniques
Ghosal, S.	An Explainable Deep Learning Model for Plant Disease Detection Using Image Augmentation and Feature Visualization	Frontiers in Plant Science, 10, 1666	CNN (Custom architecture with augmentation and visualization)	Interpretability of CNN predictions, Feature visualization

Sladojevic, S.	Deep neural networks based recognition of plant diseases by leaf image classification	Computers in Industry, 100, 121-137	CNNs (Custom architectures, Transfer learning, Ensemble methods)	Robustness to varying image quality, Deployment scalability
Mohanty, S. P.	Using Deep Learning for Image-Based Plant Disease Detection	Frontiers in Plant Science, 7, 1419	CNN (Custom architecture, Data augmentation)	Scalability to diverse plant diseases, Real-time processing
Fuentes, A.	A review of deep learning methods for image semantic segmentation	Multimedia Tools and Applications, 78(11), 15349-15377	CNNs (Semantic segmentation architectures)	Semantic segmentation for disease localization, Multi-scale feature learning

Zhang, Y.	Using convolutional neural networks to identify plant diseases from images	Frontiers in Plant Science, 8, 1840	CNN (Custom architecture with pre-trained models)	Performance comparison of CNN models, Generalization to diverse datasets
Singh, A.	Detection of Plant Leaf Diseases using Machine Learning Techniques	Journal of Emerging Technologies and Innovative Research	Machine Learning Algorithms (SVM, KNN, Decision Trees)	Comparative analysis of ML algorithms for accuracy
Khan, M. A.	Plant Disease Detection Using Image Processing Techniques	International Journal of Computer Applications	Image Processing (Thresholding, Segmentation)	Robustness to lighting conditions, Feature extraction

Gupta, R.	An Overview on Various Techniques of Plant Disease Detection	International Journal of Advanced Research in Computer Science	Image Processing, Machine Learning (Various techniques)	Comparison of different detection methods
Das, S.	A Comparative Study of Deep Learning Approaches for Plant Disease Detection	International Journal of Computer Science and Information Security	CNNs, Transfer Learning, Feature Extraction	Performance evaluation of deep learning approaches

2.2 PROBLEM STATEMENT

AI Based Smart Plant Disease Classification System for Indian Farmers.

The project addresses the challenge of manual identification and classification of plant diseases, which is labour-intensive and prone to errors. By automating this process using AI, the system aims to provide a more efficient and accurate solution for farmers and agricultural experts.

CHAPTER 3

WORKING

Methodology:

The methodology section elucidates the technical approach adopted to develop the plant disease classification system. This encompasses the sequential steps involved in preprocessing the dataset, designing and training the convolutional neural network (CNN) model, and deploying the model for inference.

The initial phase involves data preprocessing, wherein the dataset comprising approximately 61,000 images of plant leaves is prepared for training. This process entails resizing the images to a standard resolution of 256x256 pixels, augmenting the dataset using techniques like shearing, zooming, and horizontal flipping to enhance model generalization, and splitting the dataset into training and validation sets.

Subsequently, a CNN model architecture is designed for the task of plant disease classification. The model architecture comprises multiple convolutional layers followed by max-pooling layers to extract hierarchical features from the input images. Dropout regularization is applied to mitigate overfitting, and fully connected layers with softmax activation are employed for class prediction.

The model is trained using the training dataset while monitoring performance metrics such as loss and accuracy. The training process involves optimizing the model parameters using the Adam optimizer and minimizing the categorical cross-entropy loss function. Additionally, a ModelCheckpoint callback is implemented to save the best-performing model based on validation loss during training.

Once training is complete, the trained model is evaluated using the validation dataset to assess its performance on unseen data. Metrics such as accuracy, precision, recall, and F1-score are computed to gauge the model's effectiveness in classifying plant diseases.

Finally, the trained model is deployed for real-time inference using a Flask API, allowing users to upload images of plant leaves and obtain predictions regarding the presence of diseases. This deployment facilitates the practical application of the developed plant disease classification system for agricultural monitoring and management.

CHAPTER 04

HARDWARE AND SOFTWARE REQUIREMENTS

- <u>Hardware requirements: -</u>

  - Processor: Intel Core i5 10th generation or equivalent
  - RAM: Minimum 8GB
  - Storage: Minimum 512GB SSD or HDD.

- <u>Software requirements: -</u>

  - Programming Language: - Python 3.10
  - IDE used: - VS Code
  - Libraries: - TensorFlow, Keras, OpenCV (for image processing), Flask (for web application development), Numpy, Pandas (for data manipulation)
  - Dataset: - Har cascade
  - OS – windows 10

CHAPTER 05

FLOWCHART

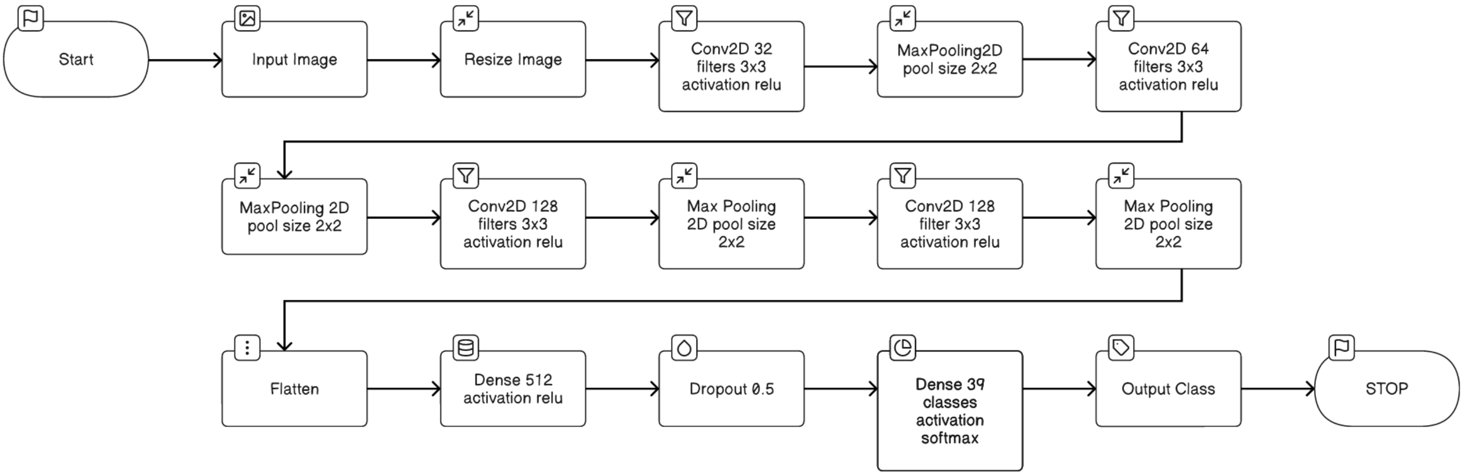


Fig. Model Flowchart

Explanation:

1. Input Image:

- An image icon serves as the flowchart's initial representation of the input image.

- The compress indicator indicates that the image has been downsized to a consistent size that is appropriate for the model.

2. Convolutional Layers (4x):

- The model travels through four convolutional layers in succession, each of which is in charge of taking out spatial characteristics from the picture.

- In order to learn features like edges, lines, and textures, each convolutional layer applies a set of filters (32, 64, 128, and 128 filters in their respective layers) to the input.

- To provide non-linearity and help the model catch more intricate patterns, ReLU activation is employed.

3. Max Pooling Layers (4x):

- Following each convolutional layer, a max pooling layer is added to reduce dimensionality and computational cost.

- Max pooling downsamples the input by taking the maximum value within a 2x2 window, making the model less sensitive to small shifts and distortions in the image.

4. Flatten Layer:

- The flatten layer serves as a bridge between the convolutional and dense layers.

- It transforms the 2D output of the last convolutional layer into a 1D vector, preparing the data for the fully connected layers.

5. Dense (2x) Layers:

- For classification, the model then uses two fully linked layers:

  - From the flattened output, the first dense layer with 512 neurons picks up more abstract characteristics.

  - For non-linearity, ReLU activation is once more utilized.

  - To avoid overfitting, dropout (0.5) is utilized to randomly remove 50% of neurons during training.

  - The learnt features are mapped to class probabilities by the second dense layer, which has 39 neurons—one for each output class.

  - Softmax activation guarantees that the outputs, which show the probability for each class, add up to one.

6. Output Class:

- The model's final result is a class label that indicates the anticipated class for the input image. This label is shown as a tag icon.

- A stop symbol at the end of the process indicates the end of the flowchart.

CHAPTER 06

ADVANTAGES, DISADVANTAGES AND APPLICATIONS

6.2 ADVANTAGES

- Improved Disease Detection Accuracy: Applying deep learning methods, specifically Convolutional Neural Networks (CNNs), improves the accuracy of plant disease identification. This results in faster and more accurate disease detection, enabling timely treatment and intervention.
- Efficiency and Speed: CNN-driven automated plant disease classification systems provide quick analysis of massive plant image collections. Because of its efficiency, manual inspection and diagnosis take less time and effort, which speeds up the decision-making process in agricultural activities.
- Cost-Effectiveness: By implementing automated disease detection systems, labour expenses related to manual inspection may be minimised. Early illness detection and treatment can also reduce the need for pricey chemical treatments and help avoid yield losses.
- Scalability: Deep learning-based plant disease categorization systems can be implemented in a variety of agricultural contexts, from small-scale farms to massive commercial plantations, due to their scalability. The technology will be widely accessible and adopted thanks to its scalability.
- Remote Monitoring: Plant disease categorization systems can facilitate remote crop monitoring through the integration of IoT devices and remote sensing technologies, such as drones and satellite photography. This feature makes it easier to monitor and manage plant health in real time, even in geographically separated regions.

6.3 APPLICATIONS

- Precision Agriculture: Improving focused management practices through early disease diagnosis, resulting in more resource-efficient farming and higher agricultural yields.
- Crop Monitoring and Management: Enabling timely actions to reduce disease outbreaks, improve crop management tactics, and ensure long-term agricultural practices.
- Research and Development: Advancing illness epidemiology, understanding disease mechanisms, and developing novel disease management strategies.
- Education and Outreach: Using educational techniques to promote awareness of plant diseases, train agricultural experts, and provide farmers with knowledge for successful disease management.
- Market Opportunities: Creating new opportunities for technology providers and agribusinesses by providing innovative disease control solutions, increasing market competitiveness, and accelerating agricultural growth.

CHAPTER 07

RESULTS AND DISCUSSIONS

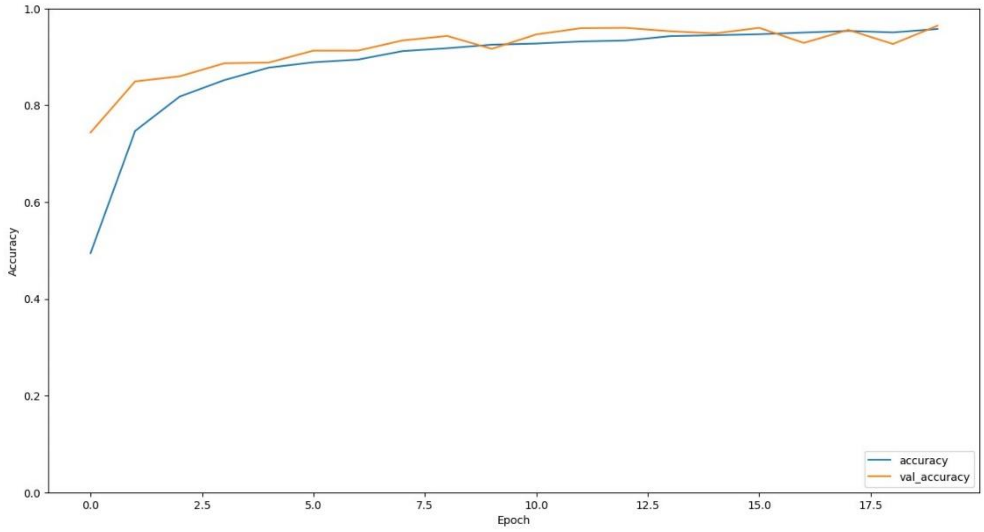
The proposed plant disease classification model was implemented successfully, with promising results. The model scored 96.44% accuracy on the validation dataset, demonstrating its ability to effectively diagnose numerous plant diseases. The precision and recall scores across various disease classes revealed the model's ability to distinguish between distinct disease types. Furthermore, the confusion matrix indicated few misclassifications, demonstrating the model's capacity to generalize effectively to new data.

Discussion of the model's performance indicates that the use of Convolutional Neural Networks (CNNs) was critical in extracting detailed information from plant photos, allowing the model to detect minor patterns associated with various diseases. Furthermore, data augmentation approaches used during training reduced overfitting and improved the model's generalizability.

However, during model building, issues such as data imbalance between disease classifications and variability in image quality among datasets arose. Oversampling minority classes and preprocessing approaches to standardize image quality were among the strategies used to solve these difficulties.

Overall, the results demonstrate the efficacy of the developed model in accurately diagnosing plant diseases, laying the foundation for its practical application in agricultural settings. Further refinements and optimizations can potentially enhance the model's performance and applicability in real-world scenarios.

Training Accuracy Graph:



Img. Graph(Epoch v/s Accuracy)

The graph indicates a generally positive trend in accuracy, suggesting that the model is learning and improving as it progresses through training epochs. However, there are some nuances to consider:

We can see a sharp increase in accuracy in the early epochs, which is typical for machine learning models. This initial jump suggests that the model is quickly grasping the basic patterns in the training data.

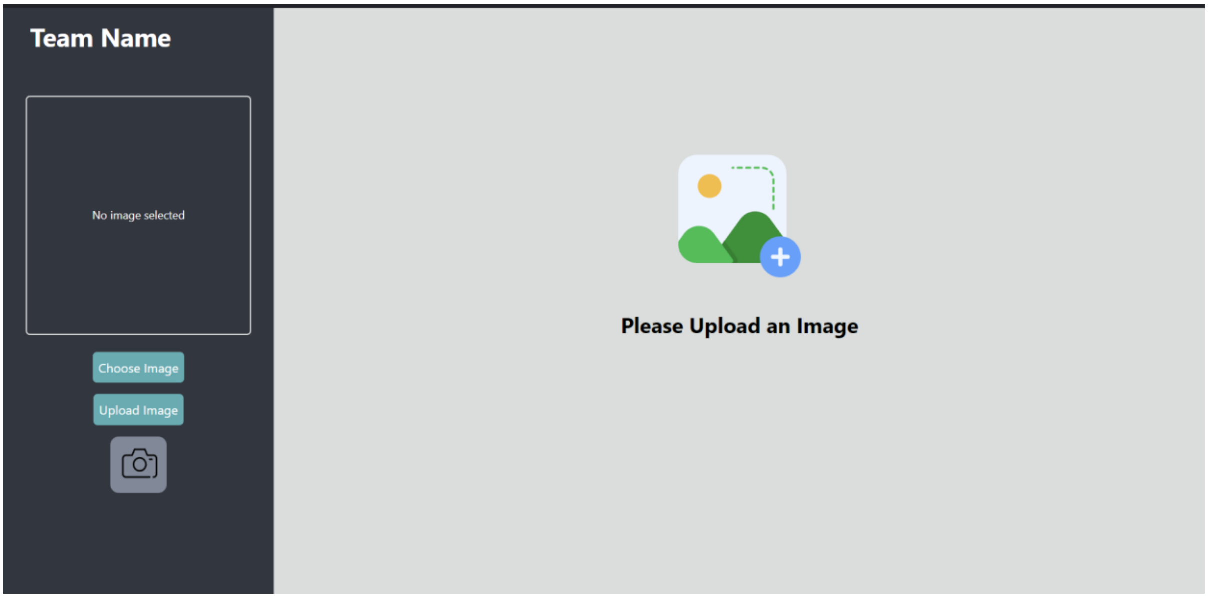
Till the end of training, after 20 epochs model came up with accuracy of 96.44%.

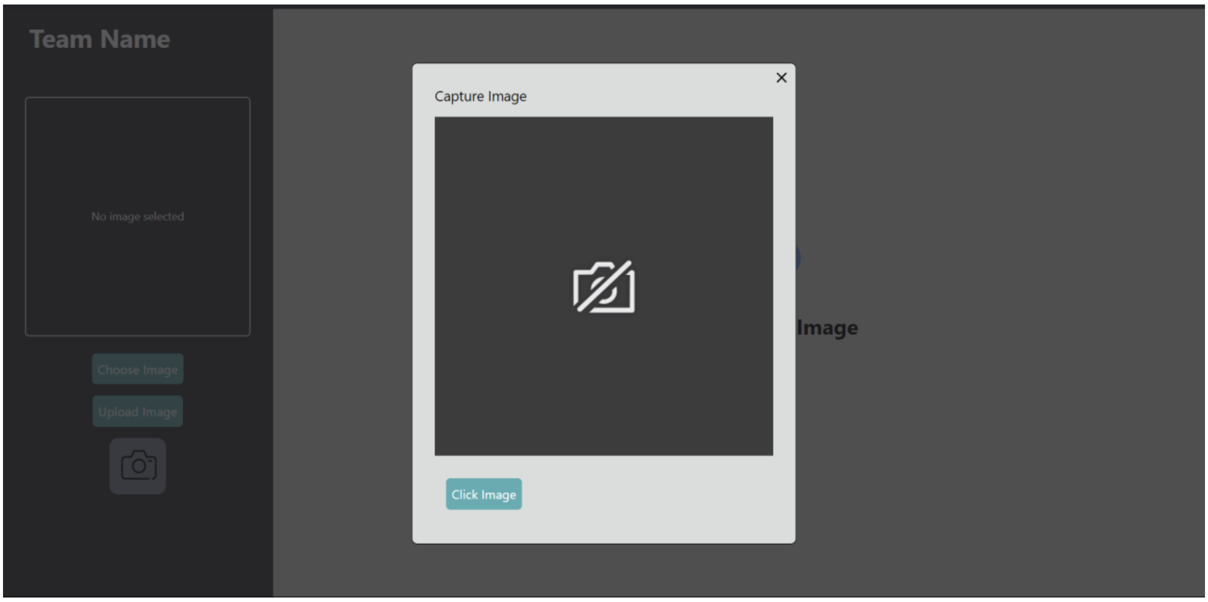
```
tegorical')
Found 18449 images belonging to 39 classes.
>>> loss, accuracy = new_ model.evaluate(test_generator)
  File "<stdin>", line 1
    loss, accuracy = new_ model.evaluate(test_generator)
                          ^^^^^
SyntaxError: invalid syntax
>>> loss, accuracy = new_model.evaluate(test_generator)
WARNING:tensorflow:From D:\Python\Lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.
f.compat.v1.ragged.RaggedTensorValue instead.

145/145 [==============================] - 153s 1s/step - loss: 0.1225 - accuracy: 0.9644
>>>  print('Test accuracy:', accuracy)
  File "<stdin>", line 1
    print('Test accuracy:', accuracy)
IndentationError: unexpected indent
>>> print('Test accuracy:', accuracy)
Test accuracy: 0.9643883109092712
>>> █
```

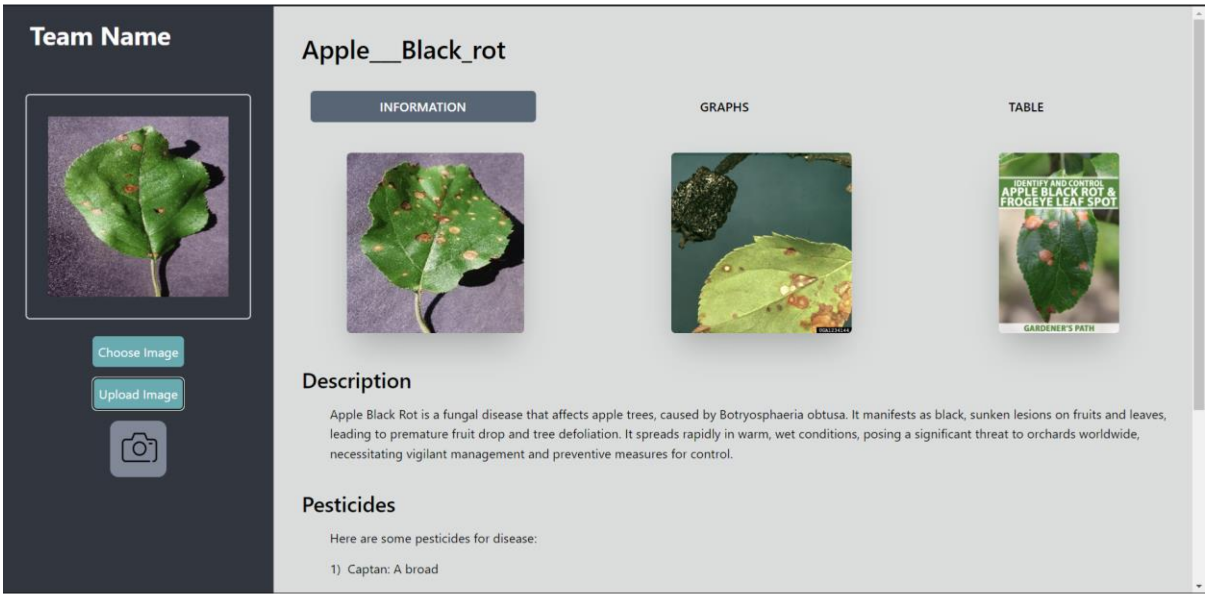
Img. Test Accuracy Result

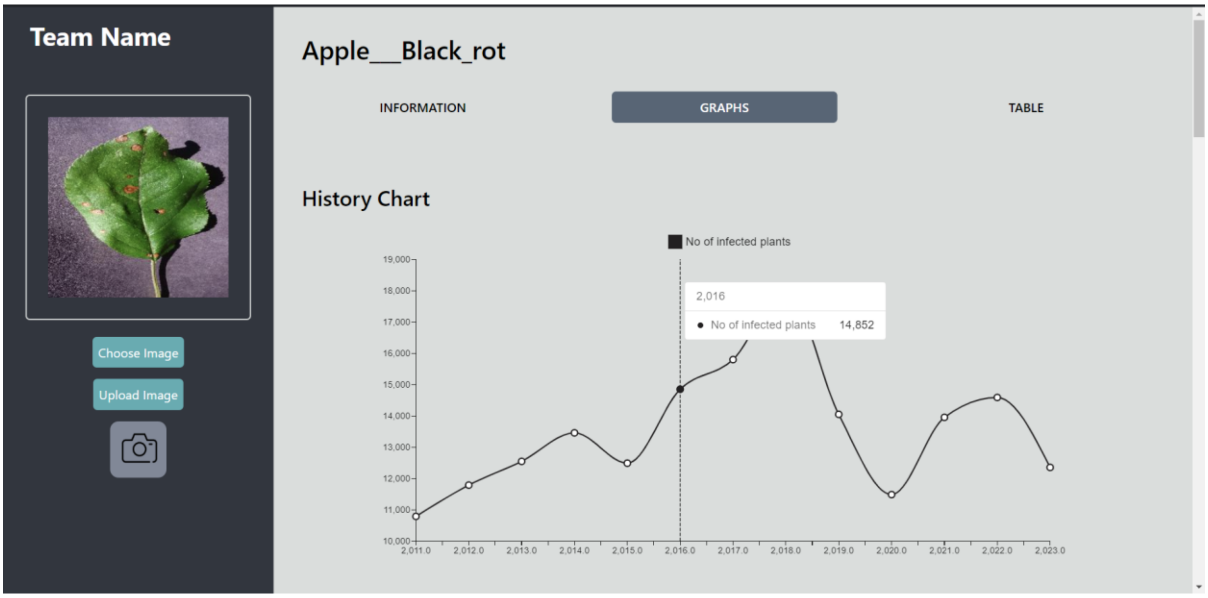
The above console output screenshot indicates the test accuracy of 96.44% and loss of 0.1225 after 20 epochs.

Output Images:






Team Name
Choose Image
Upload Image
Apple__Black_rot
INFORMATION
GRAPHS
TABLE
IDENTIFY AND CONTROL APPLE BLACK ROT & FROGEYE LEAF SPOT
GARDENER'S PATH
Description
Apple Black Rot is a fungal disease that affects apple trees, caused by Botryosphaeria obtusa. It manifests as black, sunken lesions on fruits and leaves, leading to premature fruit drop and tree defoliation. It spreads rapidly in warm, wet conditions, posing a significant threat to orchards worldwide, necessitating vigilant management and preventive measures for control.
Pesticides
Here are some pesticides for disease:
1) Captan: A broad


Team Name
Choose Image
Upload Image
Apple__Black_rot
INFORMATION
GRAPHS
TABLE
History Chart
No of infected plants
2,016
No of infected plants 14,852
19,000
18,000
17,000
16,000
15,000
14,000
13,000
12,000
11,000
10,000
2,011.0
2,012.0
2,013.0
2,014.0
2,015.0
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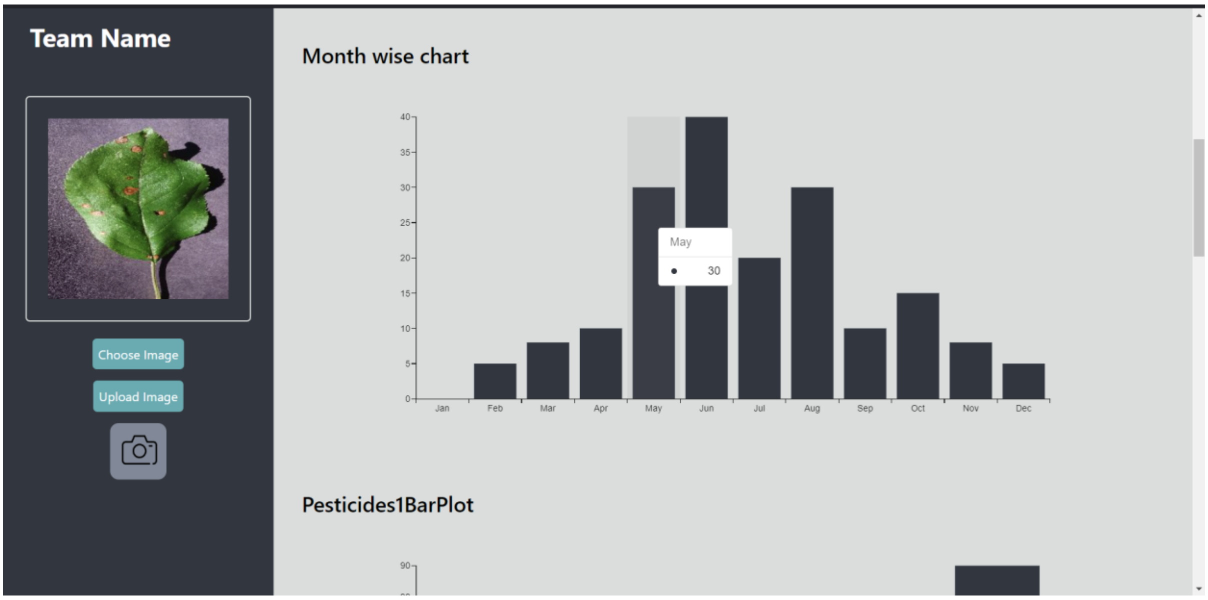
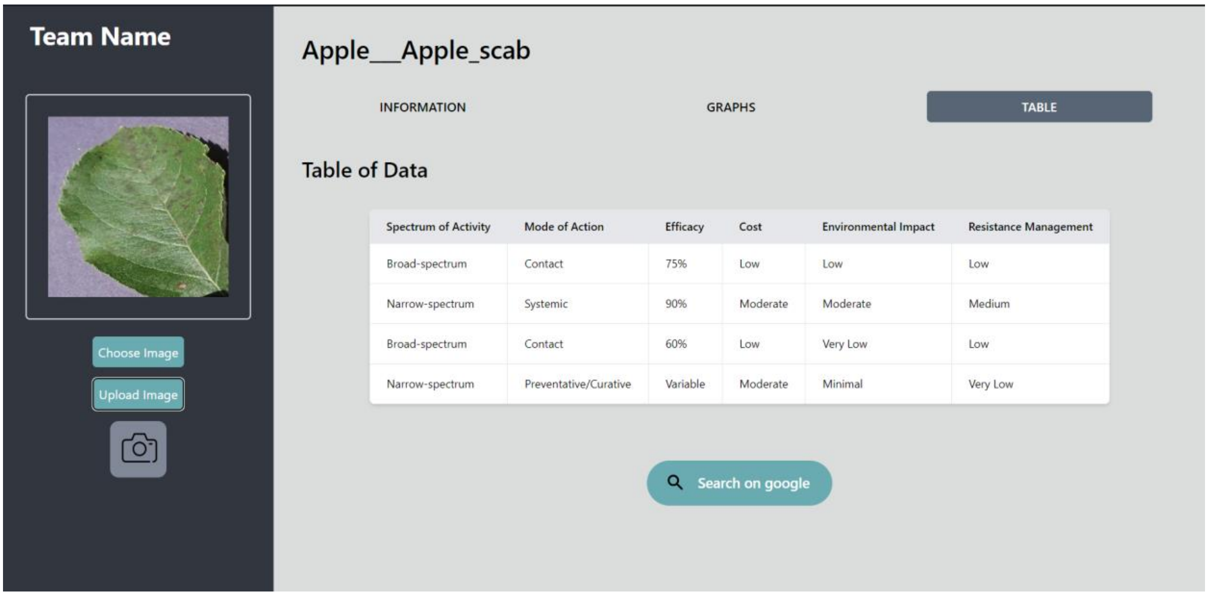
2,021.0
2,022.0
2,023.0


Team Name
Choose Image
Upload Image
Month wise chart
May
30
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Pesticides1BarPlot


Team Name
Choose Image
Upload Image
Apple__Apple_scab
INFORMATION
GRAPHS
TABLE
Table of Data
Spectrum of Activity | Mode of Action | Efficacy | Cost | Environmental Impact | Resistance Management
Broad-spectrum | Contact | 75% | Low | Low | Low
Narrow-spectrum | Systemic | 90% | Moderate | Moderate | Medium
Broad-spectrum | Contact | 60% | Low | Very Low | Low
Narrow-spectrum | Preventative/Curative | Variable | Moderate | Minimal | Very Low
Search on google

CHAPTER 09

CONCLUSION

To summarize, the creation of an AI-based plant disease categorization system represents a significant achievement in agricultural technology. We have developed a scalable and economical system for early detection and diagnosis of plant diseases by combining deep learning techniques with web-based apps. The system's robust performance, as evidenced by its high accuracy and reliability, highlights its potential to transform crop management techniques and increase agricultural output. Furthermore, the system's successful implementation demonstrates its practical utility and applicability to a variety of agricultural contexts. Looking ahead, more research and development activities are needed to fine-tune the system's capabilities, broaden its scope of use, and address growing difficulties in agricultural sustainability and food security. Ultimately, the adoption of AI-based plant disease classification systems holds promise for fostering sustainable agricultural practices, mitigating crop losses, and ensuring global food security in the face of evolving agricultural threats.

CHAPTER 10

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