Kathmandu University

Department
of
Electrical and Electronics Engineering

FINAL YEAR PRESENTATION

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Tomato Plant Disease Detection using Convolutional Neural Networks

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Presentation Outline

- Introduction
- Model Architecture
- Problem Definition
- Objective
- Significance of the Project
- Literature Review
- System Overview
- Methodology
- Results
- Gantt Chart
- Limitations
- Conclusion
- References

Introduction

- Tomato plants are highly susceptible to a variety of diseases, which can severely impact both crop yield and quality.
- Common tomato plant diseases such as Early Blight, Late Blight, Septoria Leaf Spot, Leaf Curl and more such diseases can spread rapidly, leading to significant losses if not identified and treated in a timely manner.

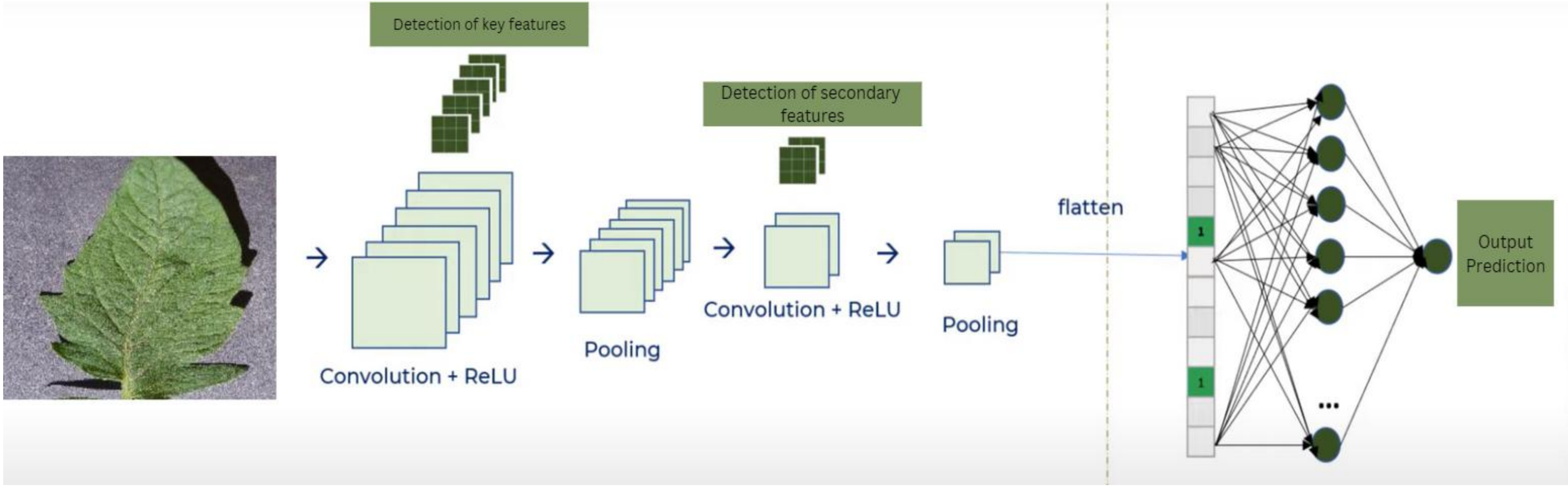
Figure: Healthy Tomato Leaf

Figure: Early Blight Tomato Leaf

Figure: Late Blight Tomato Leaf

Figure: Septorial Tomato Leaf

Model Architecture



Problem Definition

- As discussed earlier, tomato plants are susceptible to a wide range of diseases for which the detection and diagnosis of these diseases typically require expert knowledge and regular monitoring, which can be time-consuming and costly for farmers.
- Misdiagnosis or delayed detection often results in significant crop losses, negatively impacting both productivity and profitability.
- With the increasing global demand for agricultural efficiency, there is a pressing need for automated, accurate, and accessible disease detection systems that can be utilized by farmers with limited technical knowledge.

Objective

- To build a web-based tool that uses CNN to identify tomato plant diseases accurately.

Significance of the Project

- This project holds immense significance in the agricultural sector, especially in the context of precision farming and smart agriculture. By providing an automated and scalable solution for plant disease detection, the system will be able to:

    1. Improve crop health management
    2. Enhance agricultural productivity
    3. Minimize expert dependency
    4. Support sustainability
    5. Promote technological innovation in agriculture

Literature Review

- According to Mohanty et al. [1], CNNs can effectively learn to classify diseases in plants based on leaf images, surpassing traditional image processing techniques such as feature extraction and segmentation.
- One of the pioneering works in this domain is by Sladojevic et al. [2], who applied deep neural networks to classify 13 different plant diseases. Their approach achieved an overall accuracy of 96.3%.
- The study by Ferentinos [3] demonstrated the robustness of deep learning models in diagnosing plant diseases, focusing specifically on tomatoes. In their work, a CNN model was trained on the PlantVillage dataset, achieving an accuracy of up to 98% for certain diseases.

Literature Review

- Hughes and Salathé [4] also curated this dataset to encourage advancements in mobile disease diagnostics and ML-based solutions for agriculture.
- Using this dataset, researchers can train ML models to recognize diseases with high accuracy, as highlighted by Fuentes et al. [5], who applied object detection models to identify diseases in real-time, achieving promising results in recognizing pests and diseases in tomato plants.
- As noted by Too et al. [6], models trained on PlantVillage often struggle with real-world images due to variations in lighting, angle, and occlusions. This has prompted the need for data augmentation techniques to improve model robustness, which is essential for deployment in real-world applications.

System Overview

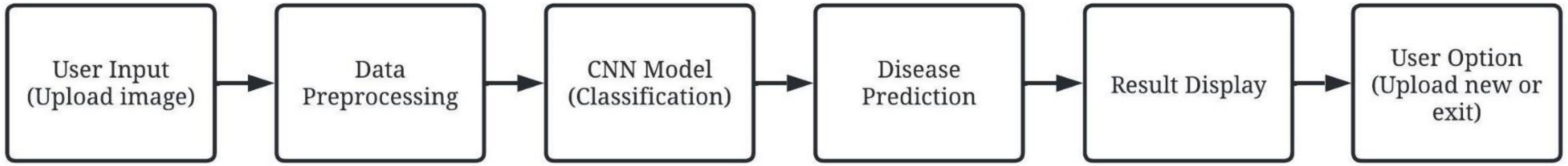


Figure: System Overview

- **User Input:** User uploads an image of a tomato plant's leaf through the web interface.
- **Data Preprocessing:** The uploaded image is resized and processed to be compatible with the CNN model. Techniques like normalization or augmentation (rotation, scaling, etc.) is applied to improve the model's performance.
- **CNN Model:** The processed image is passed into the custom Convolutional Neural Network (CNN) model. The CNN classifies the image into different disease categories.

System Overview

- **Disease Prediction:** The CNN model provides the prediction result, indicating the detected disease or that the plant is healthy.
- **Result Display:** The prediction is displayed on the user interface, showing the user the disease or health status of the plant.
- **User Options:** The user can upload a new image for diagnosis or exit the application.

Methodology

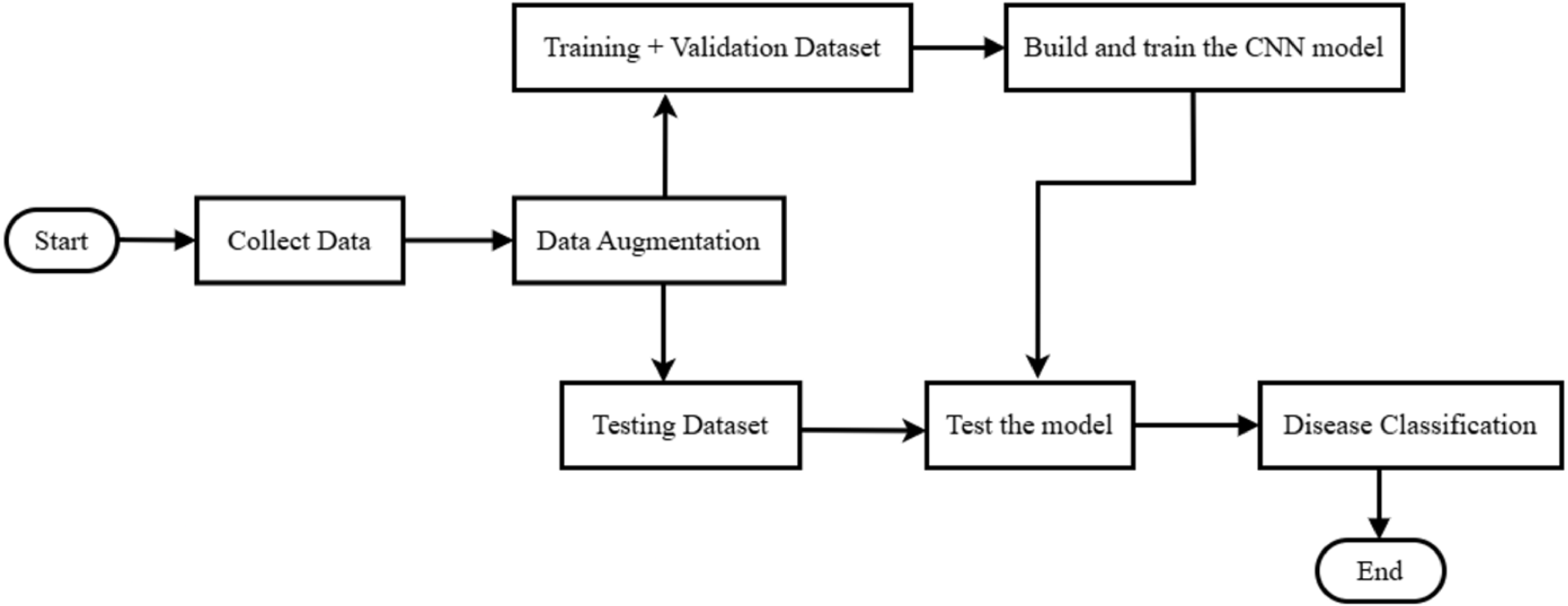
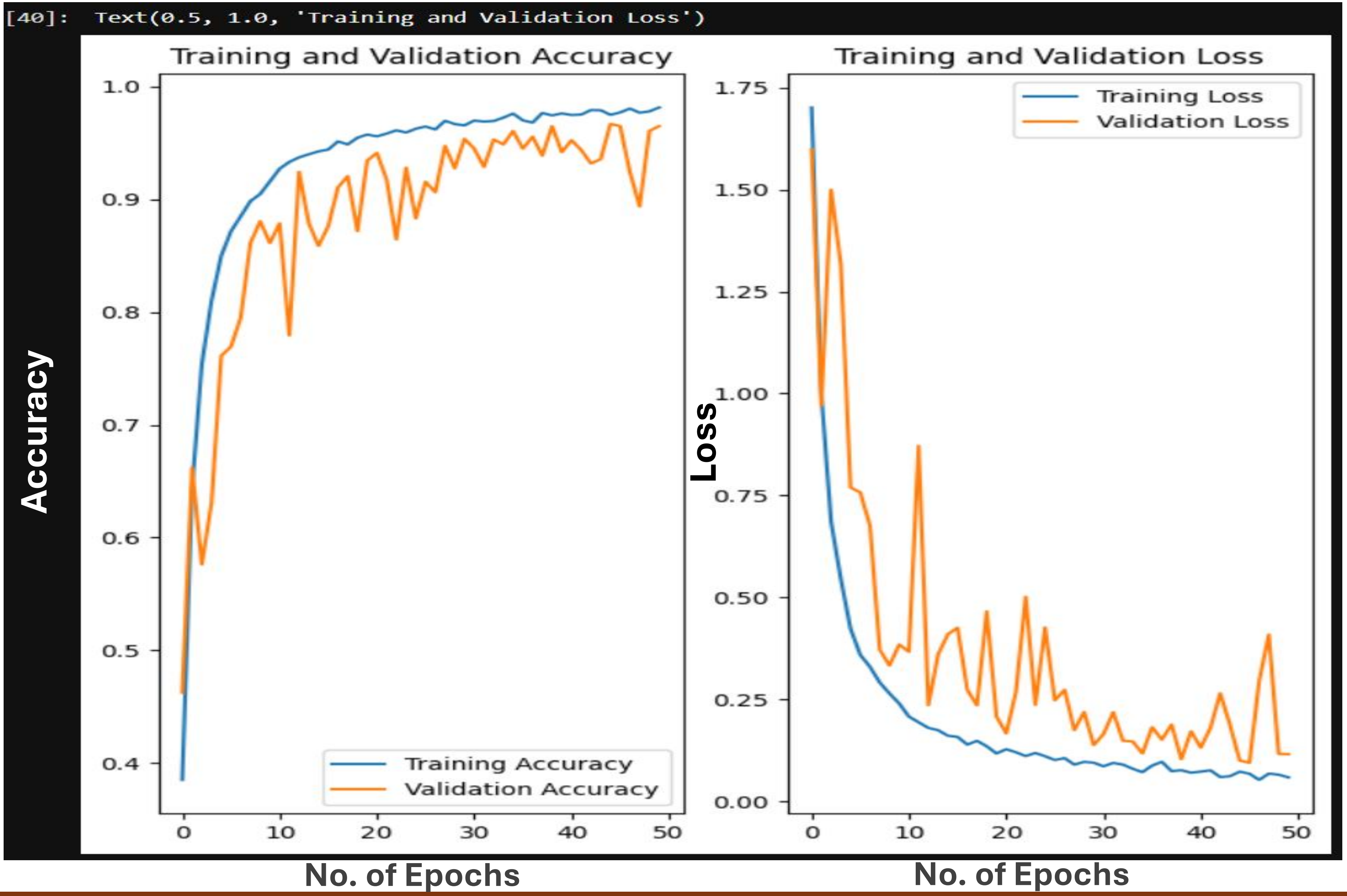


Figure: Project workflow

Work Accomplished

Visualization in Graphs

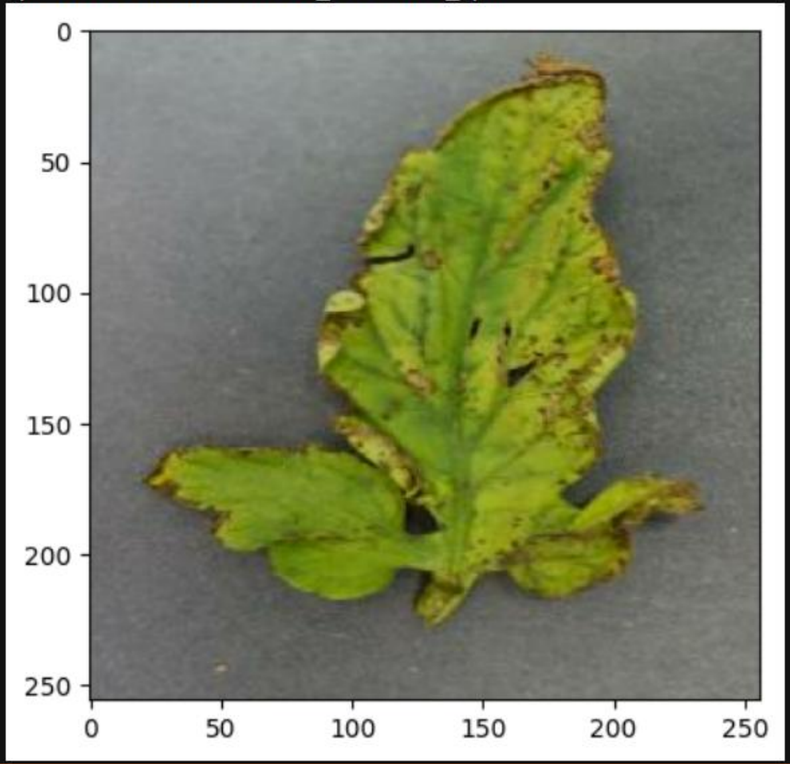


Results

Making Predictions

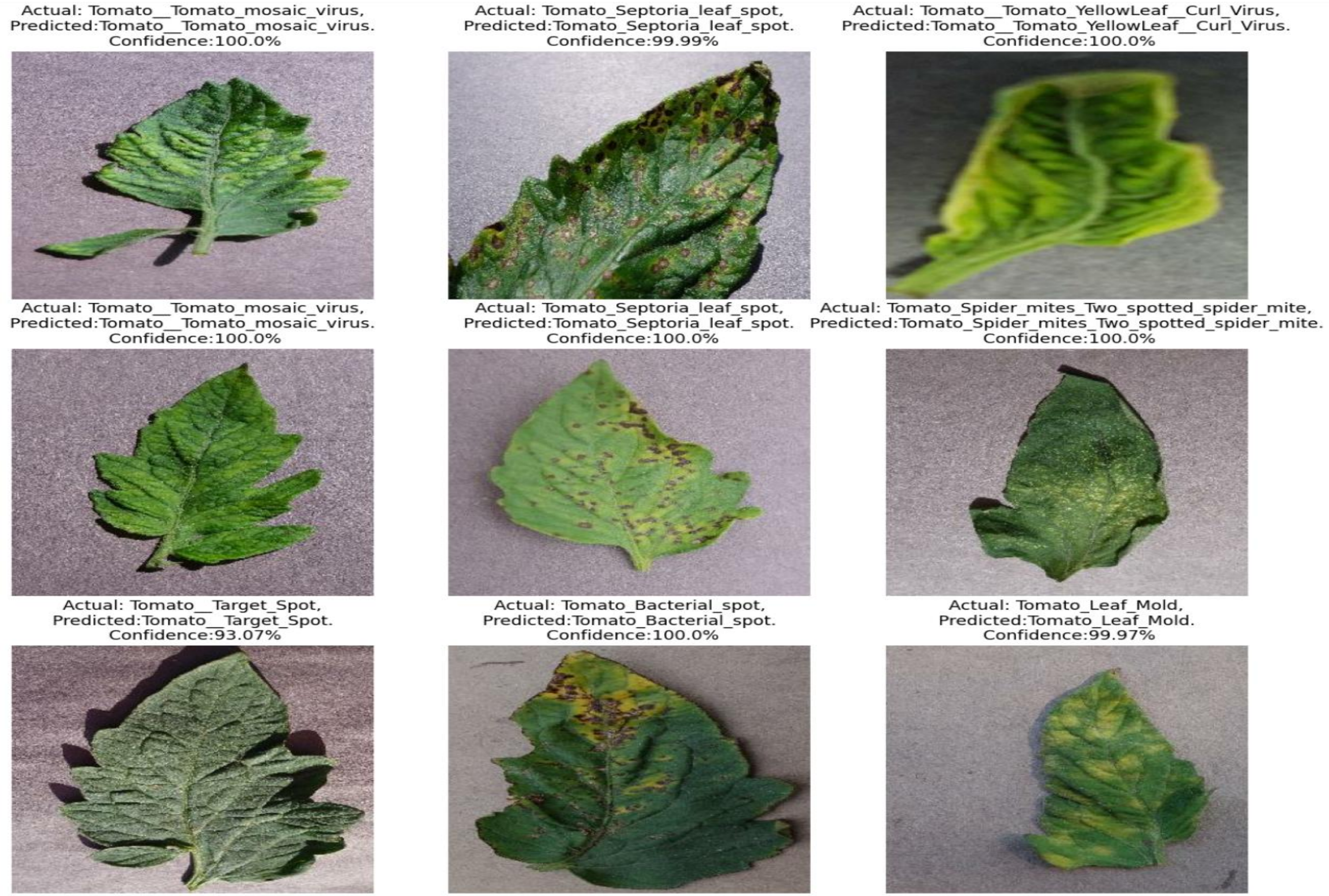
```
[57]: import numpy as np
      for images_batch, labels_batch in test_ds.take(1):
          first_image=images_batch[0].numpy().astype('uint8')
          first_label=labels_batch[0]

      print("first image to predict")
      plt.imshow(first_image)
      print("actual label: ",class_names[first_label])

      batch_prediction=model.predict(images_batch)
      print("predicted label:",class_names[np.argmax(batch_prediction[0])])
```

```
first image to predict
actual label:  Tomato_Bacterial_spot
1/1 [==============================] - 0s 29ms/step
predicted label: Tomato_Bacterial_spot
```

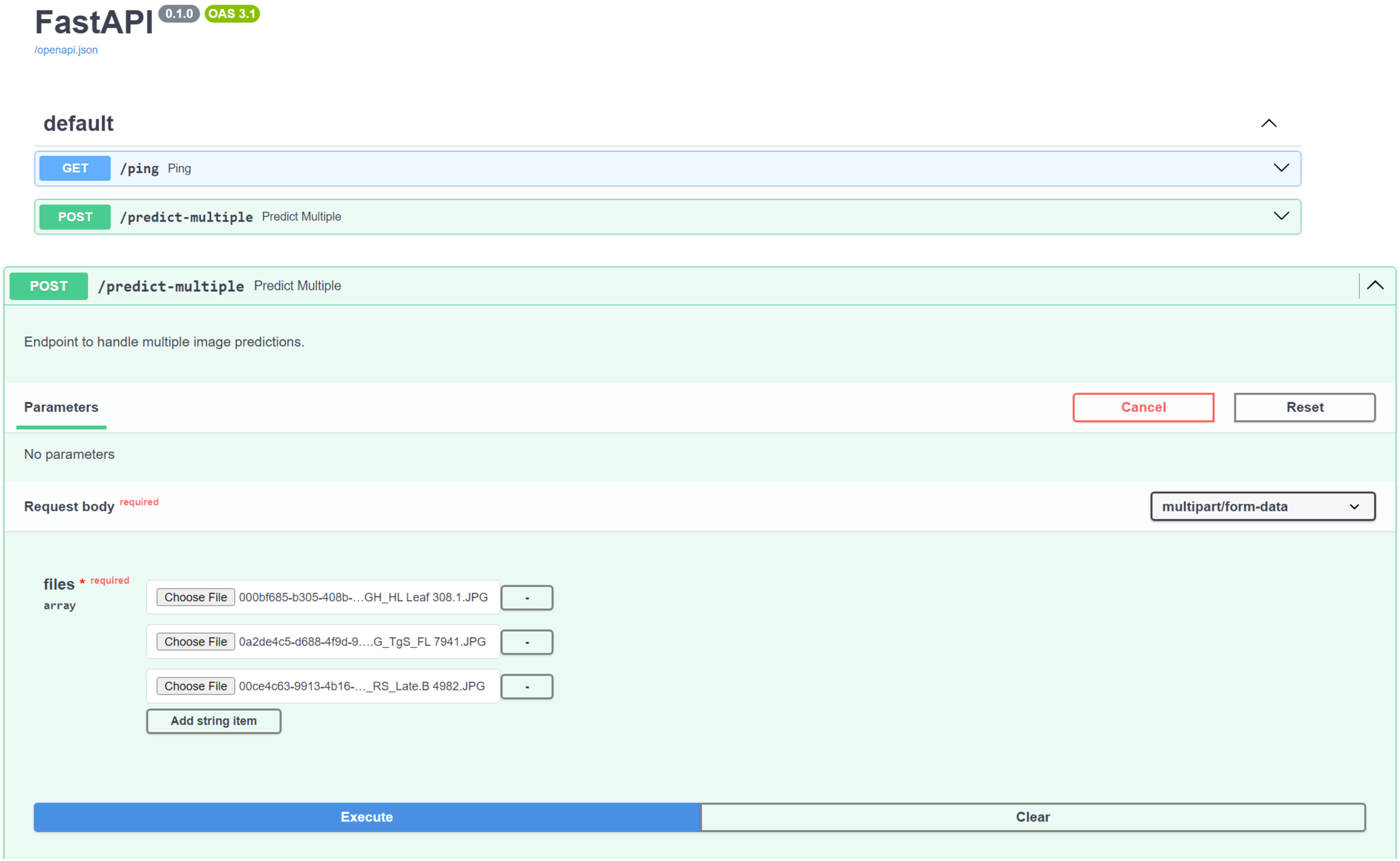


Results

Making Multiple Predictions with Confidence Levels



Results



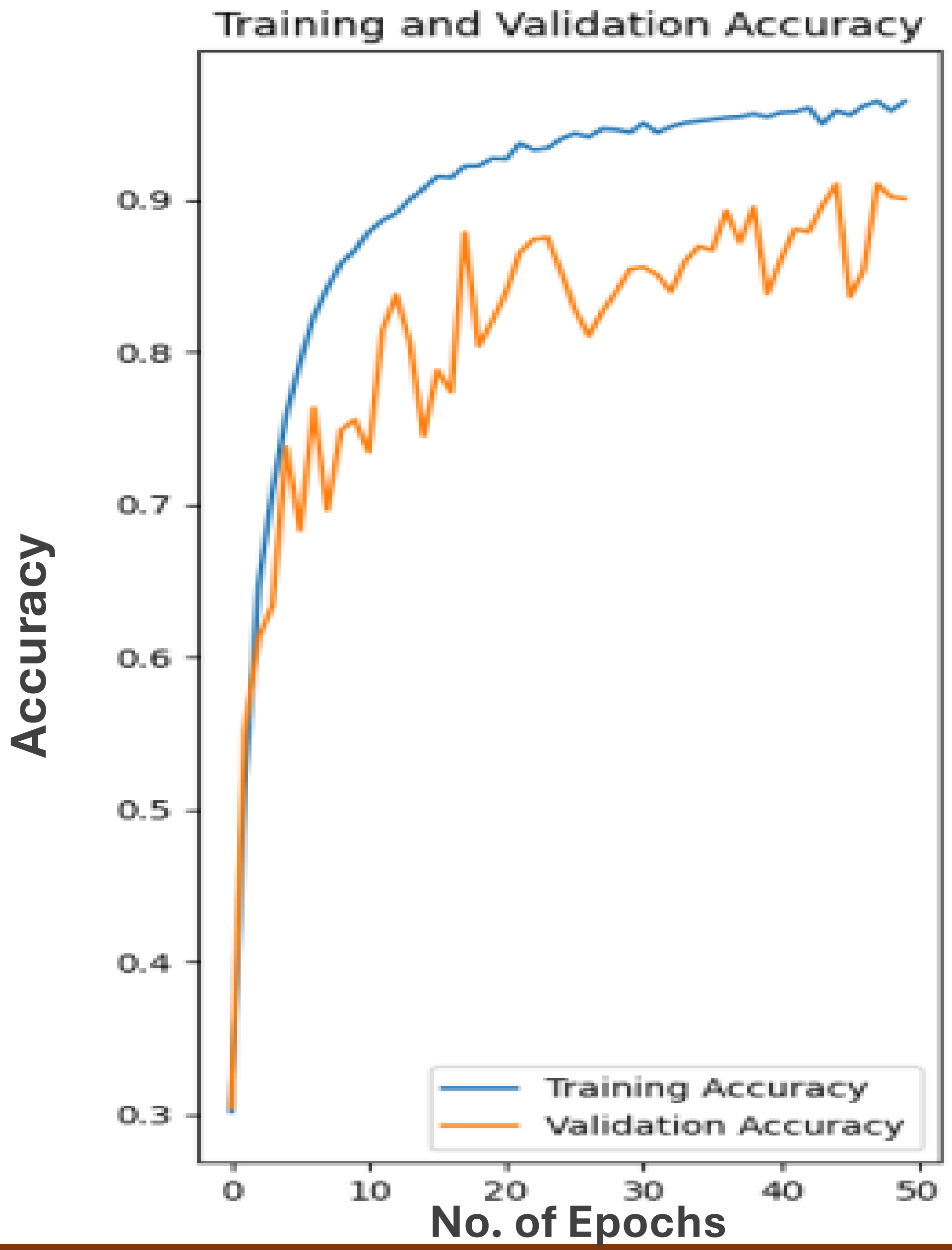
FastAPI 0.1.0 OAS 3.1
/openapi.json
default
GET /ping Ping
POST /predict-multiple Predict Multiple
POST /predict-multiple Predict Multiple
Endpoint to handle multiple image predictions.
Parameters
Cancel
Reset
No parameters
Request body required
multipart/form-data
files * required
array
Choose File 000bf685-b305-408b-…GH_HL Leaf 308.1.JPG
Choose File 0a2de4c5-d688-4f9d-9….G_TgS_FL 7941.JPG
Choose File 00ce4c63-9913-4b16-…_RS_Late.B 4982.JPG
Add string item
Execute
Clear

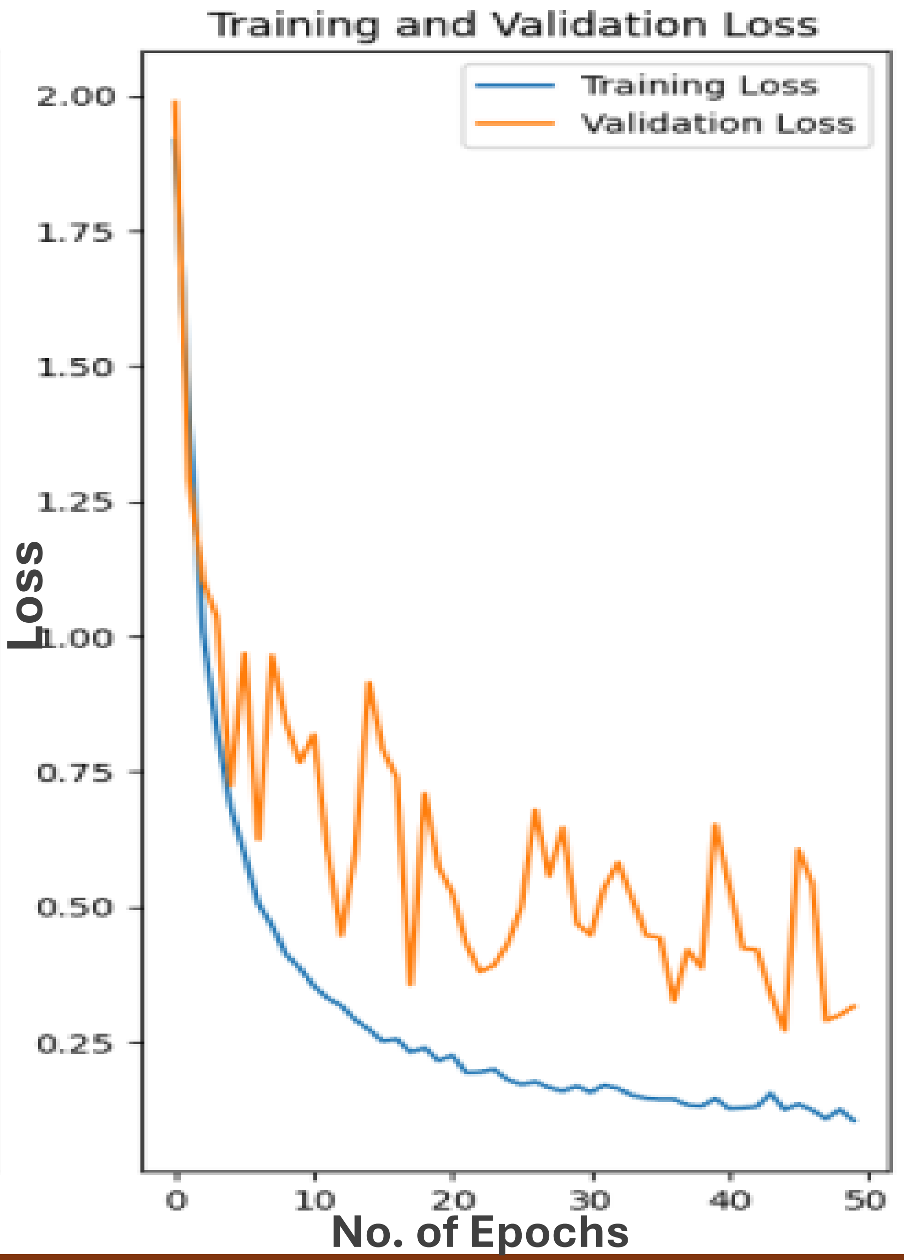
Results

Response body

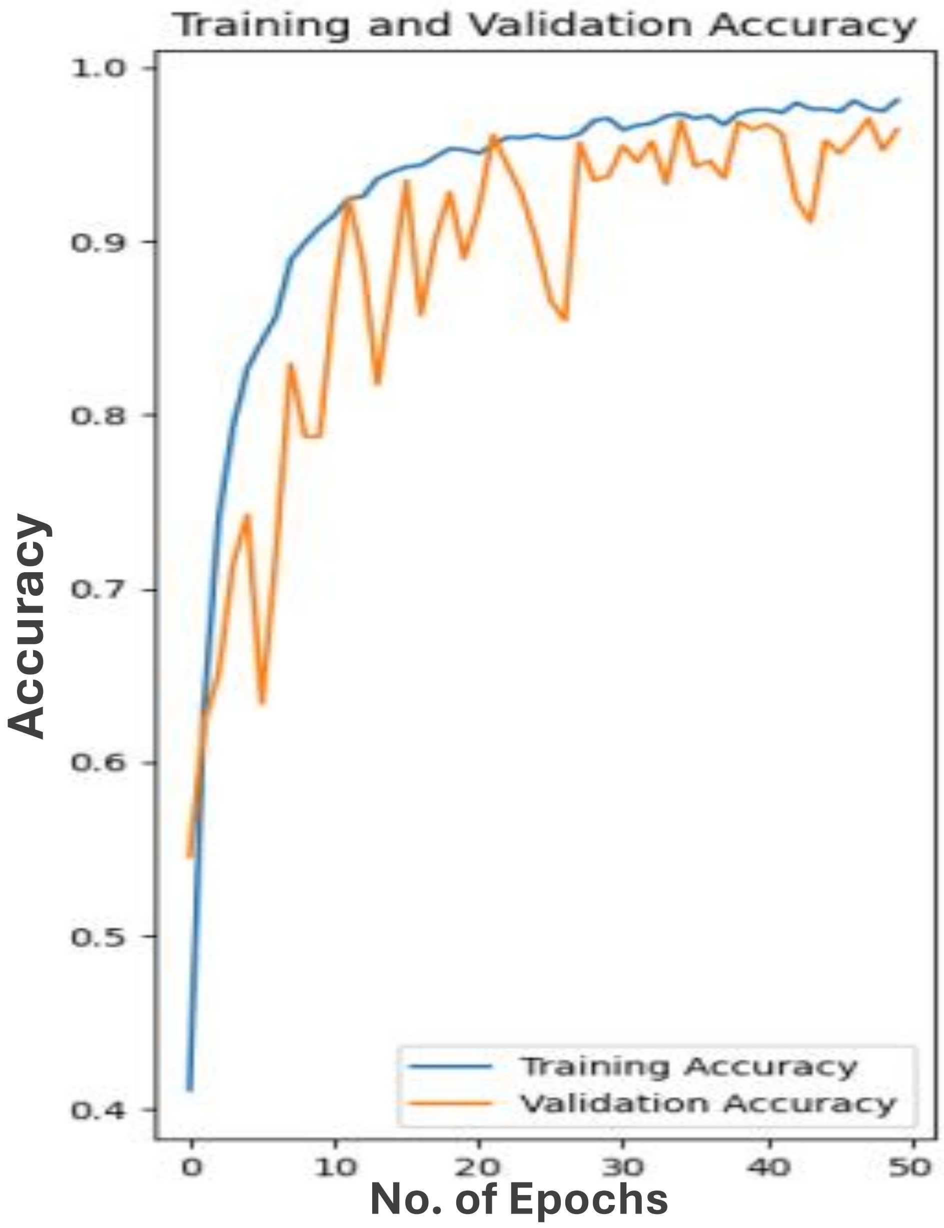

```
{
  "results": [
    {
      "filename": "000bf685-b305-408b-91f4-37030f8e62db___GH_HL Leaf 308.1.JPG",
      "class": "Tomato_healthy",
      "confidence": 0.9999951124191284
    },
    {
      "filename": "0a2de4c5-d688-4f9d-9107-ace1d281c307___Com.G_TgS_FL 7941.JPG",
      "class": "Tomato__Target_Spot",
      "confidence": 0.9999880790710449
    },
    {
      "filename": "00ce4c63-9913-4b16-898c-29f99acf0dc3___RS_Late.B 4982.JPG",
      "class": "Tomato_Late_blight",
      "confidence": 0.9961165189743042
    }
  ]
}
```

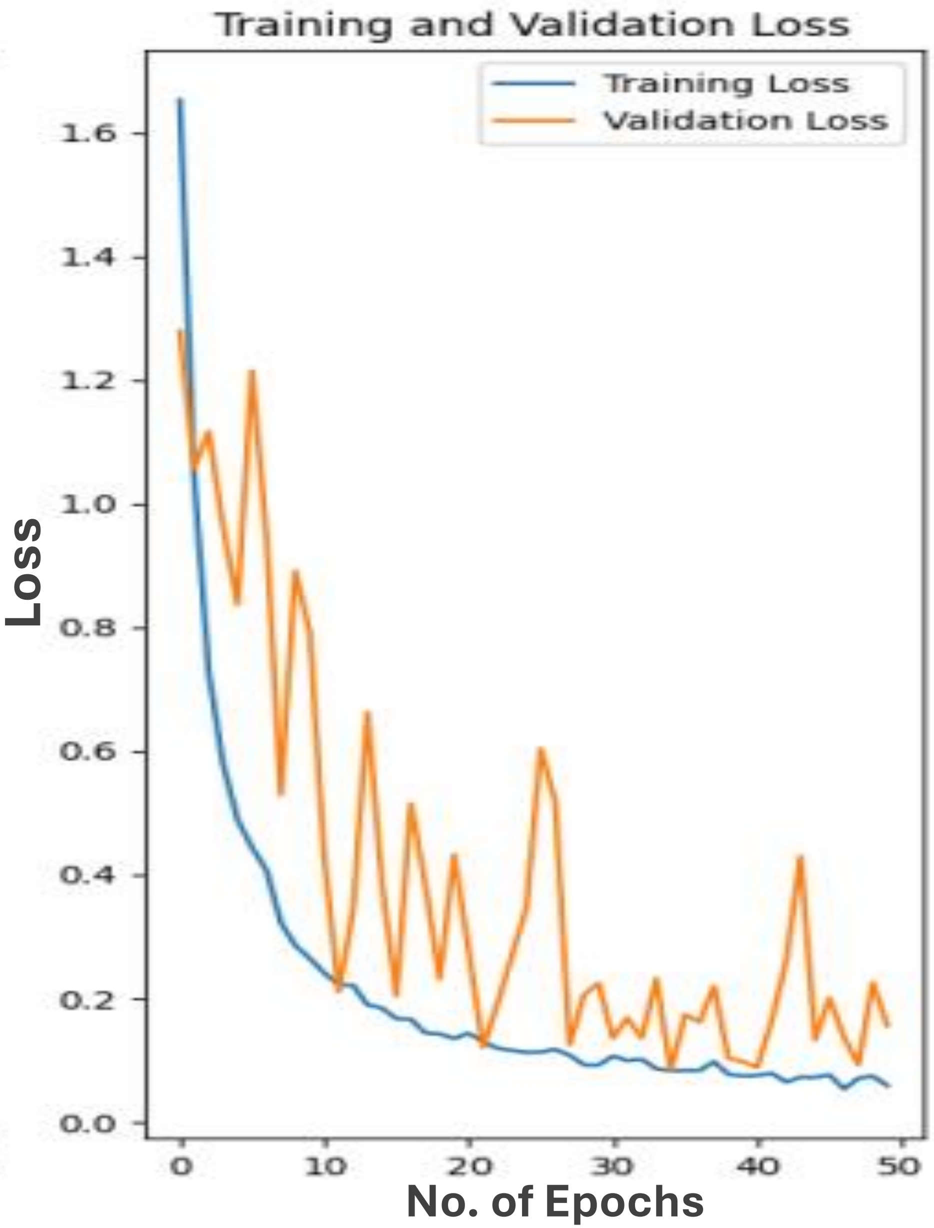
- **Dropout in the Convolutional Layers**





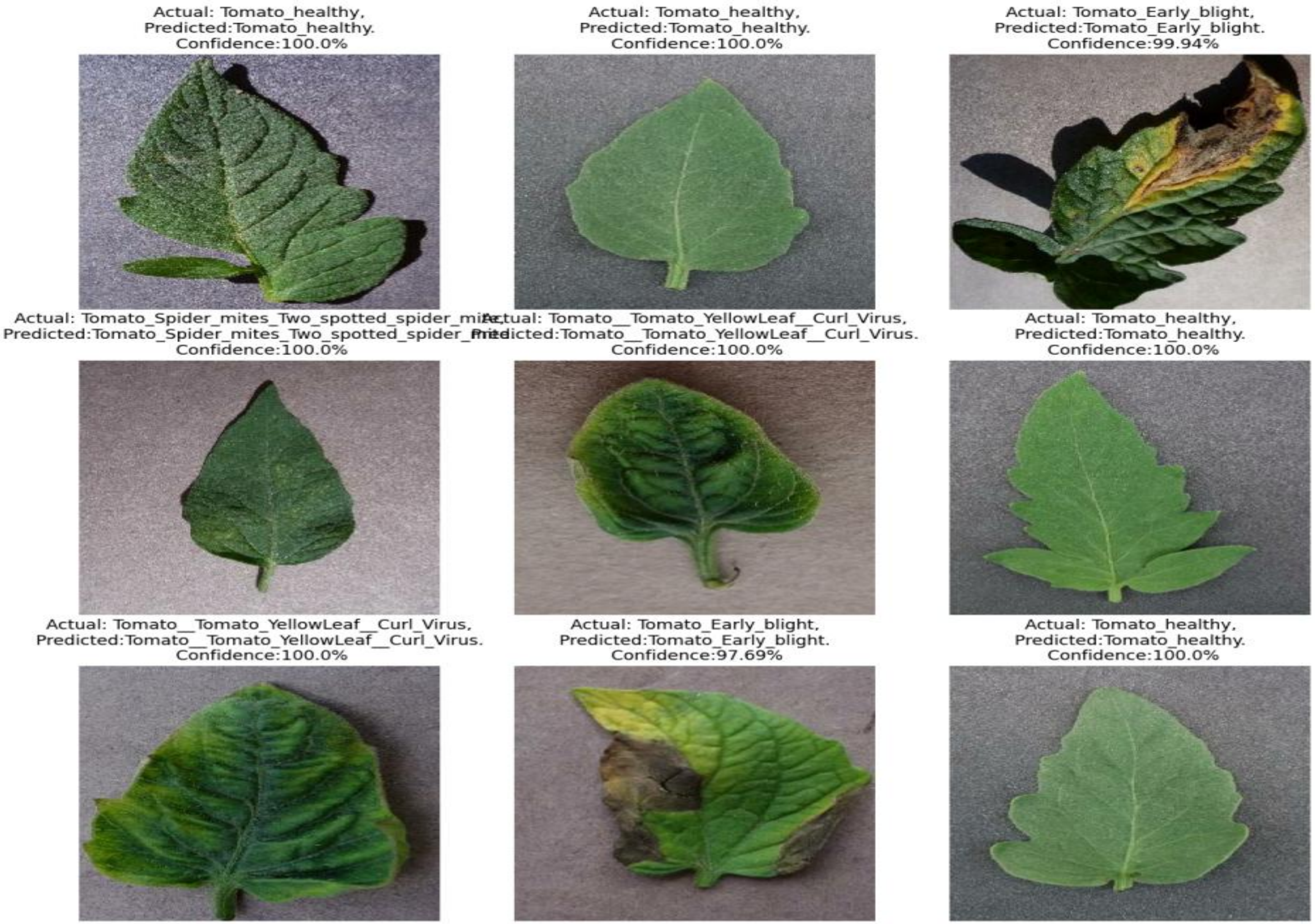
- **Dropout in the Dense Layer**





Results

- **Model Performance on one dropout layer**

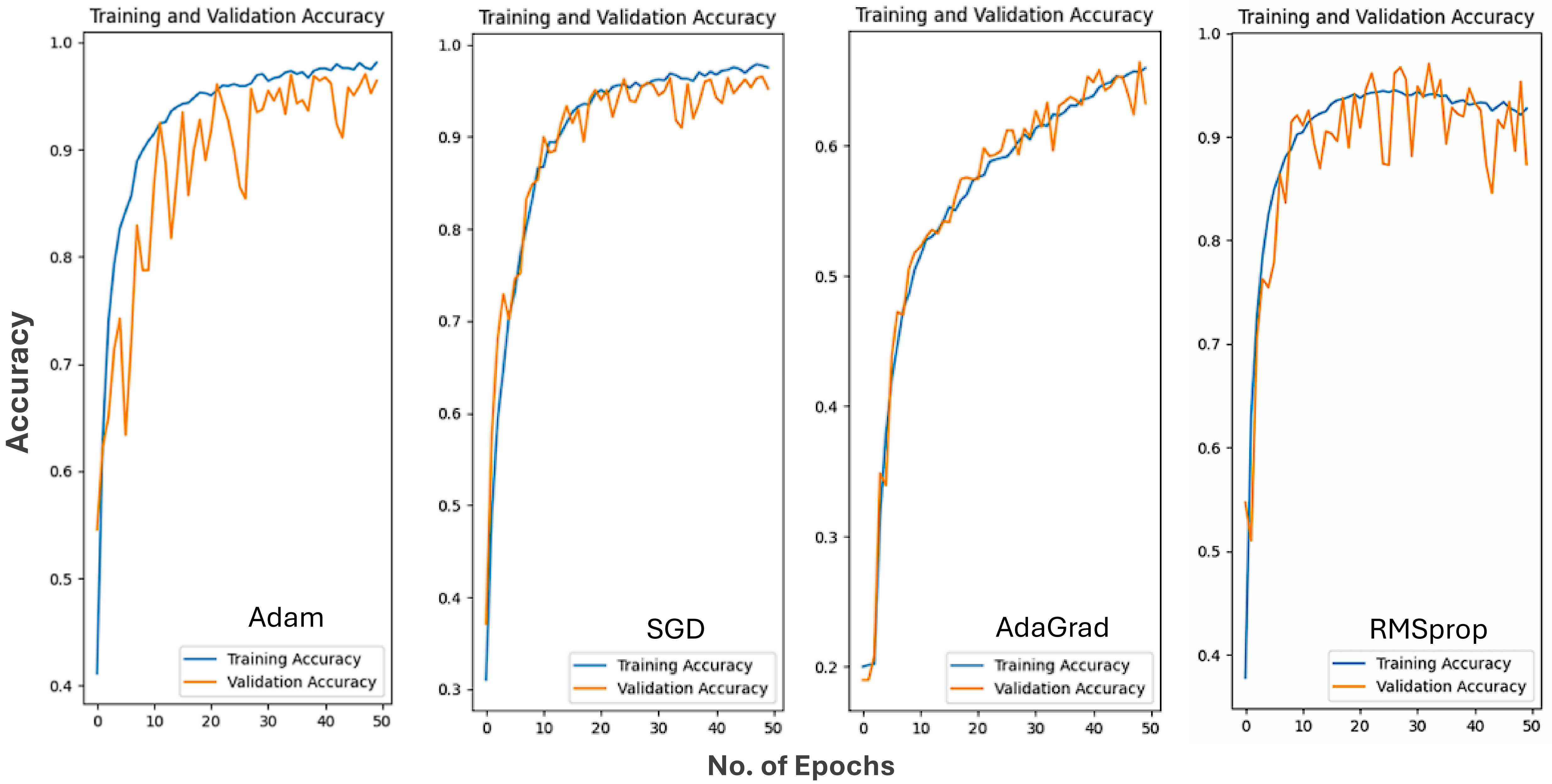


Results

- **Optimizers Comparison**

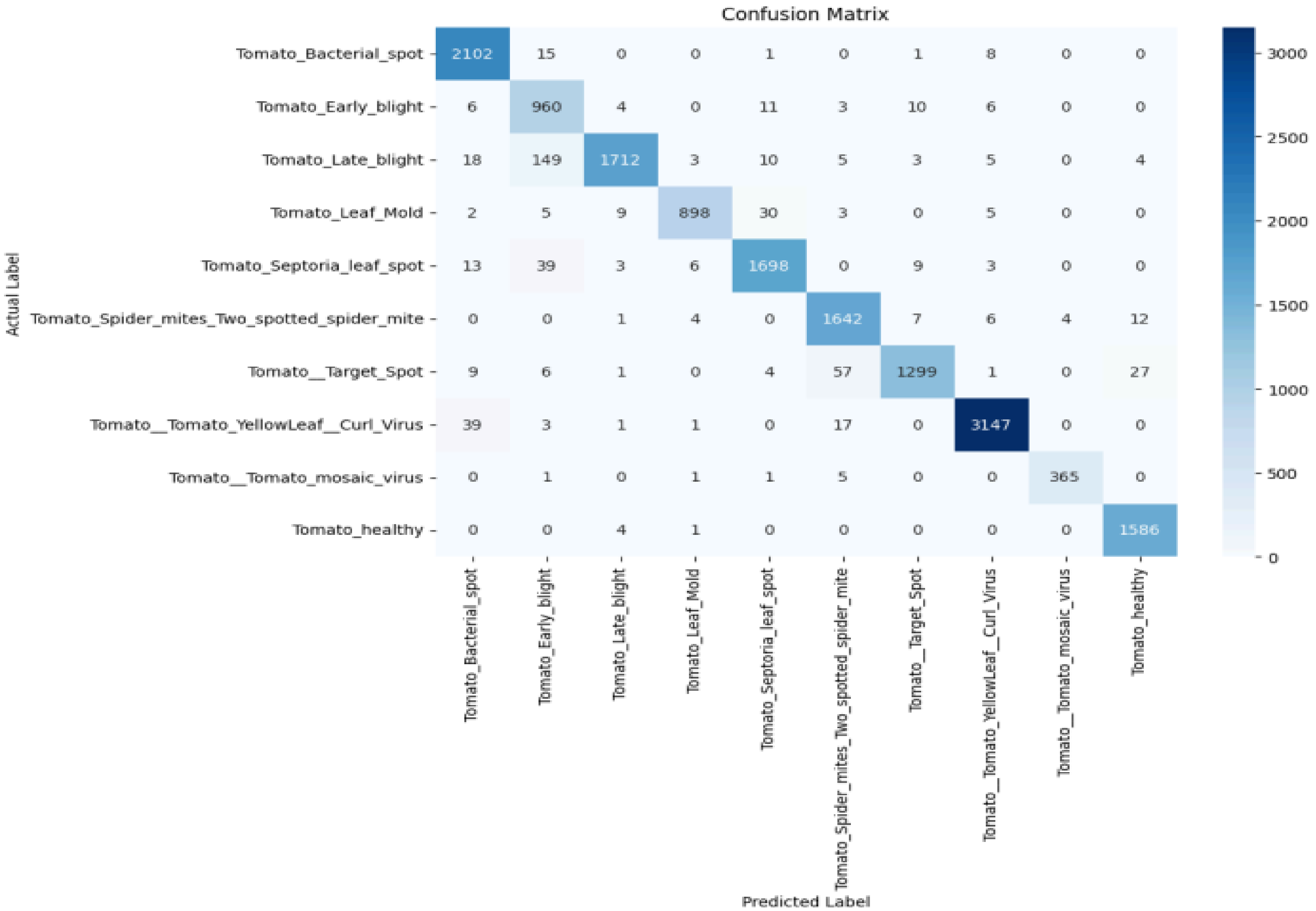
Optimizer	Accuracy	Test Dataset Accuracy
SGD	97.54%	95.71%
AdaGrad	65.97%	64.15%
Adam	98.15%	96.38%
RMSprop	92.71%	86.27%

Results



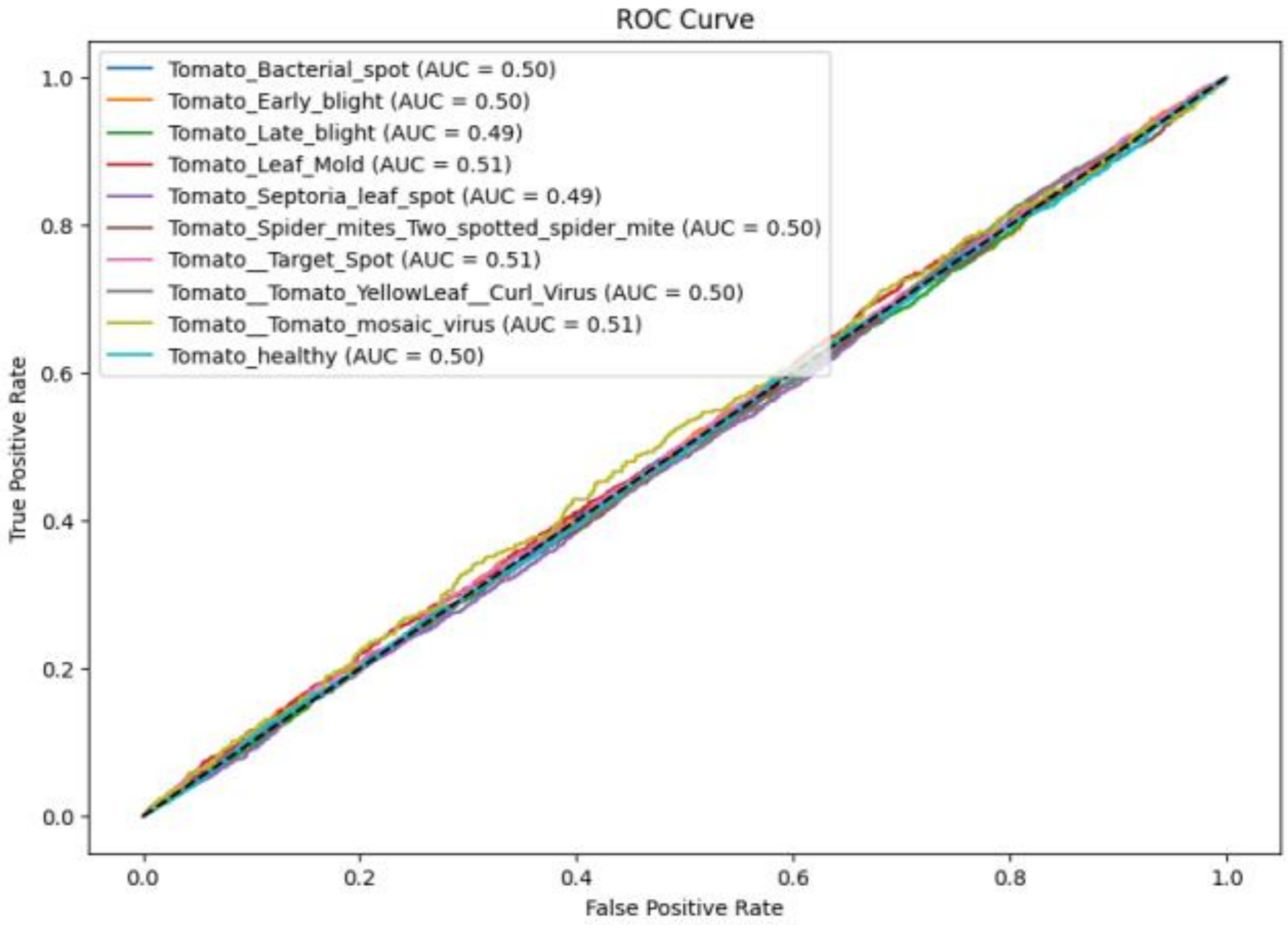
Training and Validation Accuracy
Adam
SGD
AdaGrad
RMSprop
Training Accuracy
Validation Accuracy
Accuracy
No. of Epochs

- **Confusion Matrix of the Base Model**

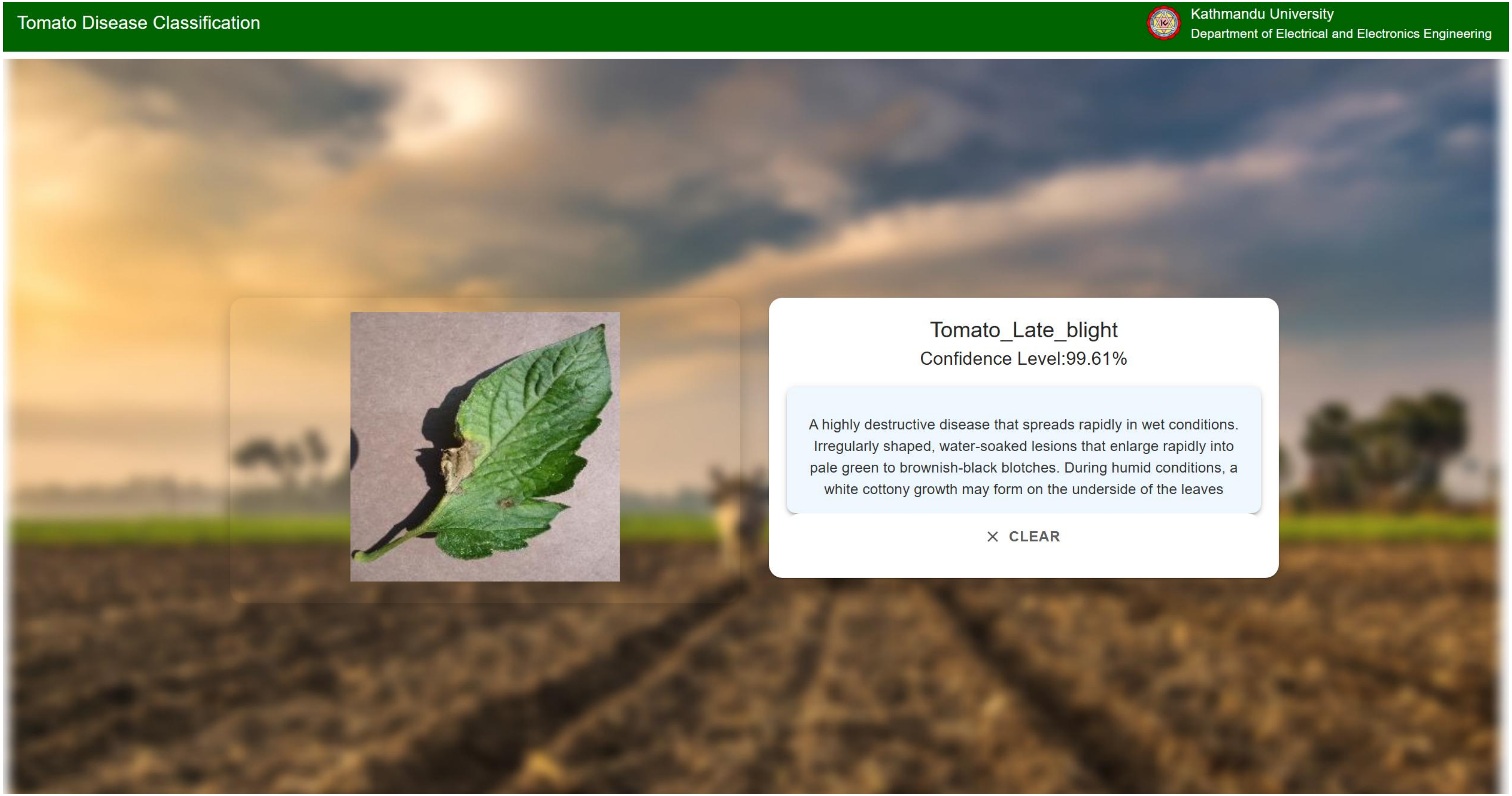


Results

- **Region of Convergence (ROC) Curve of the base model**



Results


Tomato Disease Classification
Kathmandu University
Department of Electrical and Electronics Engineering
Tomato_Late_blight
Confidence Level:99.61%
A highly destructive disease that spreads rapidly in wet conditions. Irregularly shaped, water-soaked lesions that enlarge rapidly into pale green to brownish-black blotches. During humid conditions, a white cottony growth may form on the underside of the leaves
CLEAR

Gantt Chart

Month	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr
Literature Review	■								
Proposal Writing	■								
Data Collection		■							
Data Cleaning, Preprocessing		■	■						
Model Building and Testing				■	■				
Web Development					■	■	■		
Model Integration in Local Host							■	■	
Final Testing of the Project									■

Completed	■

Limitations

- The training data may not represent real-world conditions (e.g., unseen backgrounds or lighting conditions).

Conclusion

- The project successfully demonstrates the use of Convolutional Neural Network for the detection of tomato plant diseases using images of the plant's leaf. By using a custom made model from the dataset of PlantVillage, the system was able to achieve high accuracy and strong generalization performance, providing a promising solution for early disease classification in the agricultural field. This is essentially a system typically targeted for farmers so that it helps in boosting agricultural productivity and improving crop health in the long run.

References

- [1] S. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, p. 1419, 2016.
- [2] A. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep neural networks based recognition of plant diseases by leaf image classification,” Computational Intelligence and Neuroscience, vol. 2016, 2016.
- [3] E. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311-318, 2018.
- [4] D. P. Hughes and M. Salathé, “An open access repository of images on plant health to enable the development of mobile disease diagnostics,” arXiv preprint arXiv:1511.08060, 2015.

References

- [4] D. P. Hughes and M. Salathé, “An open access repository of images on plant health to enable the development of mobile disease diagnostics,” arXiv preprint arXiv:1511.08060, 2015.
- [5] H. Fuentes, S. Yoon, S. Kim, and D. Park, “A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition,” Sensors, vol. 17, no. 9, p. 2022, 2017.
- [6] B. Too, S. E. E, and J. A. Smith, “Challenges in using plant disease detection models in real-world applications,” Journal of Agricultural Informatics, vol. 10, no. 2, pp. 45-53, 2020.
- [7] J. Shorten and T. Khoshgoftaar, “A survey on image data augmentation for deep learning,” Journal of Big Data, vol. 6, no. 1, p. 60, 2019.
- [8] J. A. Cruz, J. T. Gonçalves, and L. M. P. Lima, “Data augmentation in CNN-based applications for agriculture: A case study on tomato leaf disease classification,” IEEE Access, vol. 7, pp. 119888-119898, 2019
- [9] T. Martin, “Plantix: A mobile application for plant disease diagnosis,” Agricultural Technology, vol.

Thank You for Listening!

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