URBAN PLANT HEALTH DETECTION

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Learning Objectives

- Understand how AI can assist agriculture by identifying plant diseases early.
- Learn how to prepare and process large image datasets.
- Gain hands-on experience building CNN models from scratch.
- Learn how to:
  - Avoid overfitting with dropout and augmentation
  - Interpret performance through evaluation metrics
  - Improve results with proper tuning

Source : www.freepik.com/

Tools and Technology used

- **Platform:** Google Colab
- **Language:** Python
- **Libraries:**
  Pandas,Numpy
  TensorFlow / Keras – for deep learning
  OpenCV / PIL – for image processing
  Matplotlib / Seaborn – for visualizations
  scikit-learn – for evaluation metrics
- **Dataset Source:** Kaggle

Methodology

Dataset:

- New Plant Diseases Dataset (Augmented) from Kaggle.
- Over 87,000+ images, labeled across 38 classes (diseased and healthy conditions for multiple plants).

Steps:

1. Preprocessing:

- Resize images to a uniform shape (128x128).
- Normalize pixel values.
- Apply data augmentation: rotation, flipping, zoom.

2. Model:

- Custom CNN architecture built using Keras.
- Layers: Conv2D → MaxPooling → Dropout → Dense layers.
- Trained using categorical_crossentropy and Adam optimizer.

Methodology

3. Training & Evaluation:

- Train/validation split: 80/20.
- Epochs: 10
- Final Validation Accuracy: 91.26%

Evaluated using:

- Confusion matrix
- Classification report (Precision, Recall, F1-Score)

Problem Statement:

- Plants are highly susceptible to diseases that can spread quickly and damage entire crops. Manual diagnosis is often slow, inaccurate, and requires expert intervention, making early detection challenging.

- There is a need for a fast, automated, and accurate solution to detect plant diseases from leaf images to prevent contamination and reduce crop loss.

Solution:

- Develop a deep learning-based image classification model that can detect whether a plant leaf is healthy or diseased.
- Use a large dataset of labeled images to train a model that generalizes well across multiple plant types and diseases.
- Provide early warnings so farmers can isolate diseased plants and take preventive measures.

Screenshot of Output:

```
Epoch 1/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 594s 334ms/step - accuracy: 0.3157 - loss: 2.4554 - val_accuracy: 0.7506 - val_loss: 0.8253
Epoch 2/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 348s 198ms/step - accuracy: 0.7098 - loss: 0.9317 - val_accuracy: 0.8506 - val_loss: 0.4846
Epoch 3/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 347s 197ms/step - accuracy: 0.7921 - loss: 0.6593 - val_accuracy: 0.8793 - val_loss: 0.3715
Epoch 4/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 348s 198ms/step - accuracy: 0.8282 - loss: 0.5361 - val_accuracy: 0.8876 - val_loss: 0.3524
Epoch 5/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 339s 193ms/step - accuracy: 0.8551 - loss: 0.4541 - val_accuracy: 0.8931 - val_loss: 0.3371
Epoch 6/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 355s 202ms/step - accuracy: 0.8761 - loss: 0.3863 - val_accuracy: 0.9252 - val_loss: 0.2300
Epoch 7/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 343s 195ms/step - accuracy: 0.8907 - loss: 0.3422 - val_accuracy: 0.9122 - val_loss: 0.2705
Epoch 8/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 343s 195ms/step - accuracy: 0.9010 - loss: 0.3035 - val_accuracy: 0.9386 - val_loss: 0.1911
Epoch 9/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 334s 190ms/step - accuracy: 0.9069 - loss: 0.2888 - val_accuracy: 0.9306 - val_loss: 0.2185
Epoch 10/10
1758/1758 ━━━━━━━━━━━━━━━━━━━━ 333s 189ms/step - accuracy: 0.9126 - loss: 0.2683 - val_accuracy: 0.9324 - val_loss: 0.2093
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file forma
439/439 ━━━━━━━━━━━━━━━━━━━━ 65s 148ms/step
```

This screenshot shows that after 10 epochs, the model achieved a training accuracy of 91.26% and a validation accuracy of 93.24%, with training loss reduced to 0.2683 and validation loss to 0.2093, indicating strong performance and effective learning without overfitting.

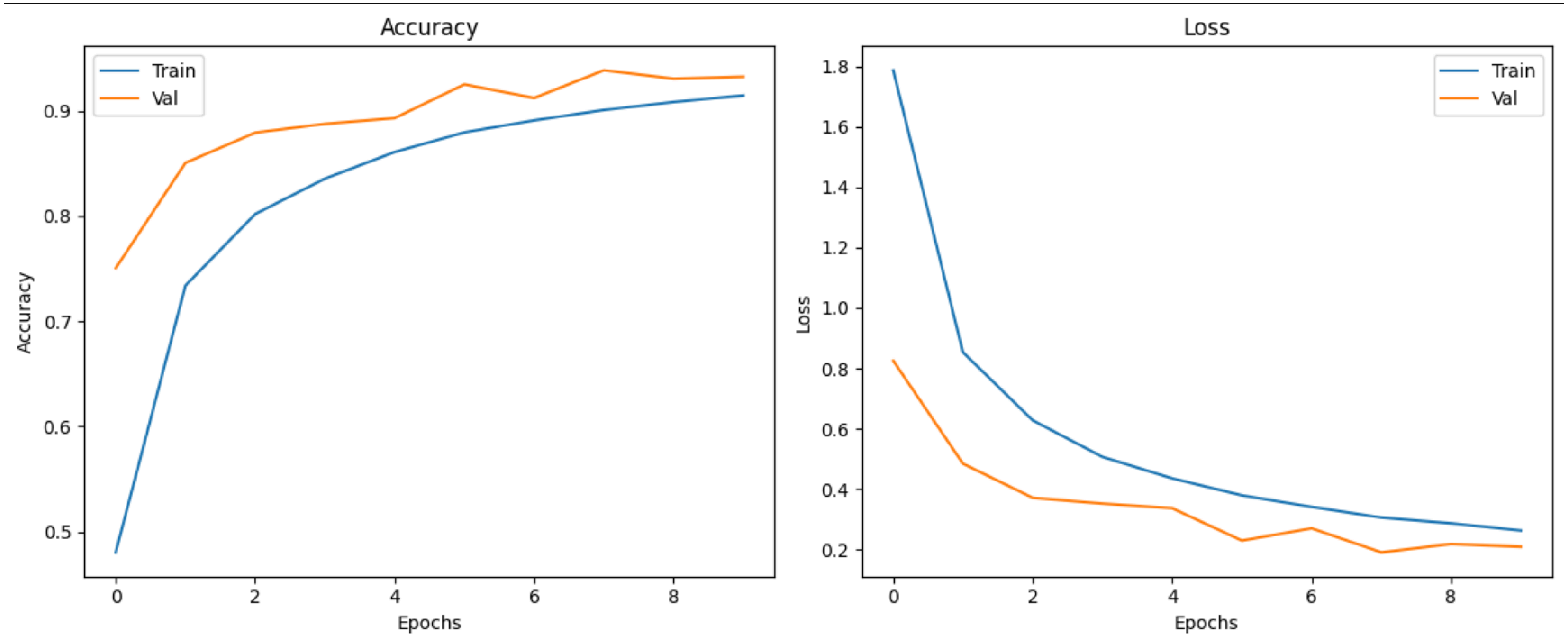
Screenshot of Output:

```
Classification Report:
                                                    precision    recall  f1-score   support

                                 Apple___Apple_scab       0.93      0.92      0.92       403
                                  Apple___Black_rot       0.97      0.97      0.97       397
                           Apple___Cedar_apple_rust       0.98      0.96      0.97       352
                                    Apple___healthy       0.94      0.83      0.88       401
                                Blueberry___healthy       0.97      0.86      0.91       363
           Cherry_(including_sour)___Powdery_mildew       0.99      0.95      0.97       336
                  Cherry_(including_sour)___healthy       0.92      0.98      0.94       365
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot       0.88      0.91      0.90       328
                        Corn_(maize)___Common_rust_       0.98      0.99      0.99       381
                Corn_(maize)___Northern_Leaf_Blight       0.95      0.89      0.92       381
                             Corn_(maize)___healthy       0.99      1.00      1.00       371
                                  Grape___Black_rot       0.96      0.94      0.95       377
                       Grape___Esca_(Black_Measles)       0.96      0.98      0.97       384
         Grape___Leaf_blight_(Isariopsis_Leaf_Spot)       0.99      0.98      0.98       344
                                    Grape___healthy       0.97      0.99      0.98       338
           Orange___Haunglongbing_(Citrus_greening)       0.99      0.98      0.99       402
                             Peach___Bacterial_spot       0.97      0.90      0.93       367
                                    Peach___healthy       0.99      0.94      0.96       345
                      Pepper,_bell___Bacterial_spot       0.94      0.95      0.95       382
                             Pepper,_bell___healthy       0.92      0.92      0.92       397
                              Potato___Early_blight       0.95      0.97      0.96       387
...
                                           accuracy                           0.93     14044
                                          macro avg       0.93      0.93      0.93     14044
                                       weighted avg       0.94      0.93      0.93     14044
```

This classification report shows a high-performing model with an overall accuracy of 93%, demonstrating strong precision, recall, and F1-scores across multiple plant disease categories.

Screenshot of Output:



The graphs show that the model's training and validation accuracy steadily increased, reaching over 91%, while the loss consistently decreased, indicating effective learning and good generalization.

Conclusion:

- Built a plant disease detection system using CNN with an accuracy of 91.26%.
- The model is capable of detecting multiple diseases across 38 different classes.
- Can help farmers intervene early and reduce crop loss.

Future Enhancements:

- Integration with drone imaging
- Expansion to more crops and real-field images

Github link- https://github.com/Abhishek220704/plant-disease-app