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AI IN PLANT DISEASES IDENTIFICATION

SUBJECT CODE : NM1067

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Content

Abstract

- Applying a deep learning image classification model, this research attempts to address the issue of identifying plant diseases.
- A massive dataset of over 87,000 RGB photos of 16 distinct types of plants, both healthy and ill, was used to train the algorithm.
- CNNs are used in the research to precisely identify diseases at the picture level and classify characteristics.
- The aim of the solution is to assist agronomists and farmers with a rapid, precise, and easily adaptable detection of diseases.
- It is expected that automating the diagnosis process will enhance harvest quality, lessen the demand for expert employees and lessen crop damage.

Problem Statement

- Farmers in many agricultural places especially rural ones, and suffer to get prompt and accurate illnesses diagnosis.
- Because hand inspection is subjective and lacks expertise, it frequently results in incorrect disease detection.
- Different diseases' early symptoms can look physically identical, which can result in incorrect treatment and more crop damage.
- Incorrect or delayed diagnosis increase pesticide use, decreases productivity of crops, and generates losses in money.
- The need for an automated, technology-driven system that can accurately and swiftly identify plant diseases from images of plants is increasing.

Introduction:

- Identifying Plant Disease Using Trained CNN Model

- Agriculture plays a crucial role in sustaining the global economy, and early detection of plant diseases is vital for ensuring crop health and maximizing yield. Traditionally, disease identification relies on human expertise, which is time-consuming and error-prone. In this project, we leverage deep learning techniques to automate the identification of plant diseases from leaf images.

- We use custom CNN, a lightweight convolutional neural network pre-trained on ImageNet, to classify plant images into 16 different disease categories. The dataset is preprocessed by resizing and normalizing images. The model is trained and validated on a subset of the PlantVillage dataset, and its performance is evaluated using accuracy metrics, confusion matrices, and visualizations.

- This approach provides an efficient and scalable solution for real-time plant disease detection, supporting smarter and more sustainable agricultural practices.

Objective

- To design and develop an image-based deep learning model capable of identifying plant diseases with high accuracy and efficiency.
- To utilize a comprehensive and labeled dataset of plant leaves for model training and evaluation.
- To apply preprocessing and data augmentation techniques to enhance the quality and diversity of the training data.
- To reduce the reliance on human expertise for plant disease diagnosis and make it accessible via digital tools.
- To contribute to sustainable agriculture by enabling early detection, timely treatment, and better crop health management.

Proposed Solution (Methodology)

- Deep Learning Approach (CNN)
- Model Used: Convolutional Neural Network (CNN) with transfer learning
- Architecture: The architecture used is AlexNet, a deep convolutional neural network designed for image classification with multiple convolutional, pooling, and dense layers
- Input: Preprocessed plant leaf images (64X64 RGB images)
- Output: Multiclass classification (16 plant disease categories)
- Frameworks: TensorFlow, Keras
- Loss Function: categorical_crossentropy
- Optimizer: Adam
- Activation Functions: ReLU (hidden layers), Softmax (output layer)

Implementation and Result Analysis

a) Implemented with Model Training in Dataset:

- CNN pre-trained on Image was used as the base model for plant disease classification.
- Training: The model was trained on a dataset of plant images labeled with 15 different disease types. Images were preprocessed by resizing and normalizing them before training.

b) Implemented with Graphical Visualization Using Matplotlib:

- Plotted the accuracy and loss over epochs for both training and validation sets.
- Generated a confusion matrix heatmap using Seaborn to assess model performance across different disease categories.

Implemented with model training in dataset

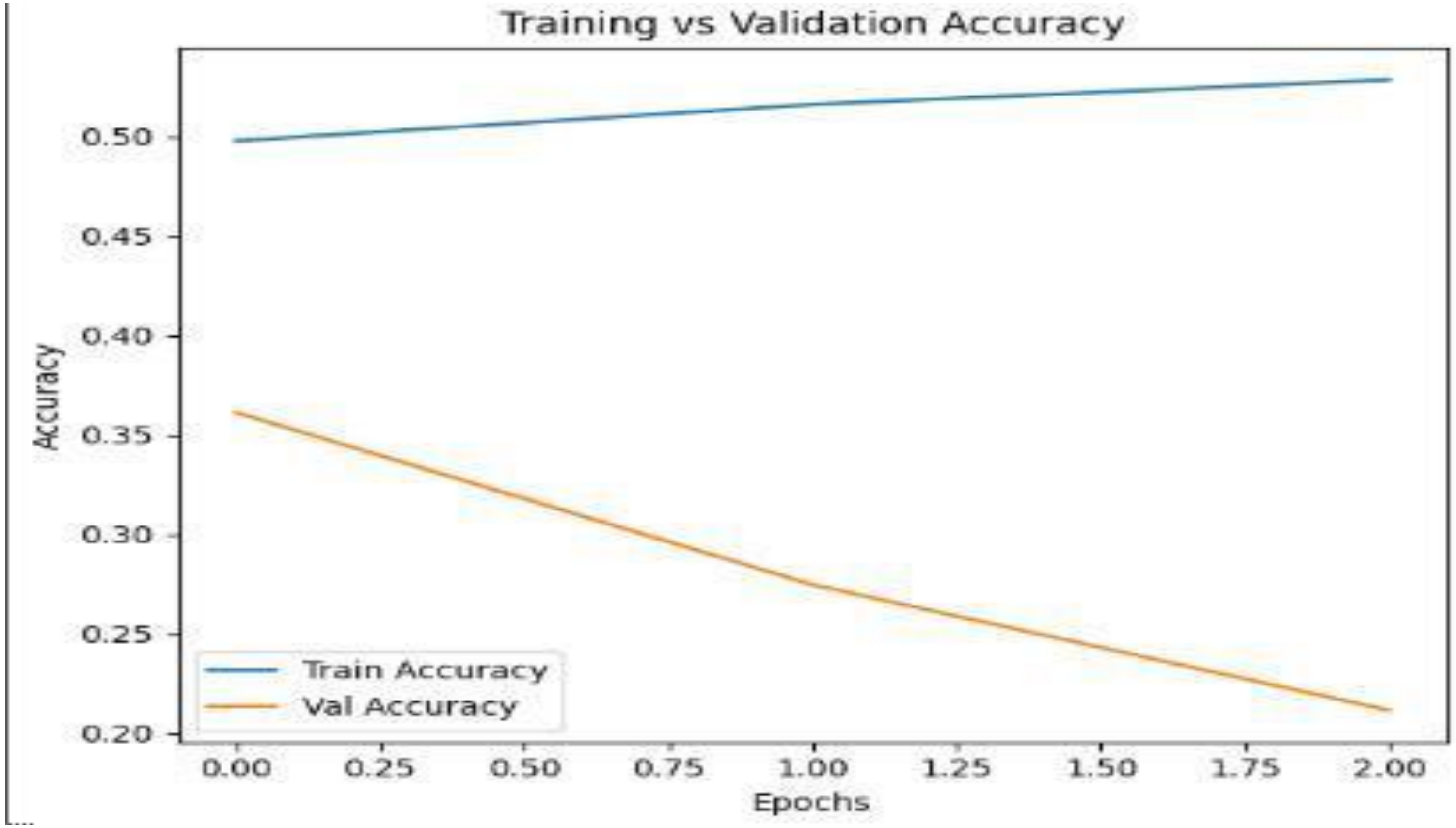
```
c:\Users\ADMIN\AppData\Local\Programs\Python\Python310\lib\site-packages\keras\src\trainers\data_adapters\py_dataset_adapter.py:121: UserWa
  self._warn_if_super_not_called()
Epoch 1/3
1033/1033 ━━━━━━━━━━━━━━━━━━━━ 755s 726ms/step - accuracy: 0.4879 - loss: 1.9750 - val_accuracy: 0.4051 - val_loss: 1.6060
Epoch 2/3
1033/1033 ━━━━━━━━━━━━━━━━━━━━ 251s 243ms/step - accuracy: 0.5061 - loss: 1.4344 - val_accuracy: 0.2175 - val_loss: 1.6647
Epoch 3/3
1033/1033 ━━━━━━━━━━━━━━━━━━━━ 136s 132ms/step - accuracy: 0.5227 - loss: 1.2512 - val_accuracy: 0.2648 - val_loss: 1.5689
```

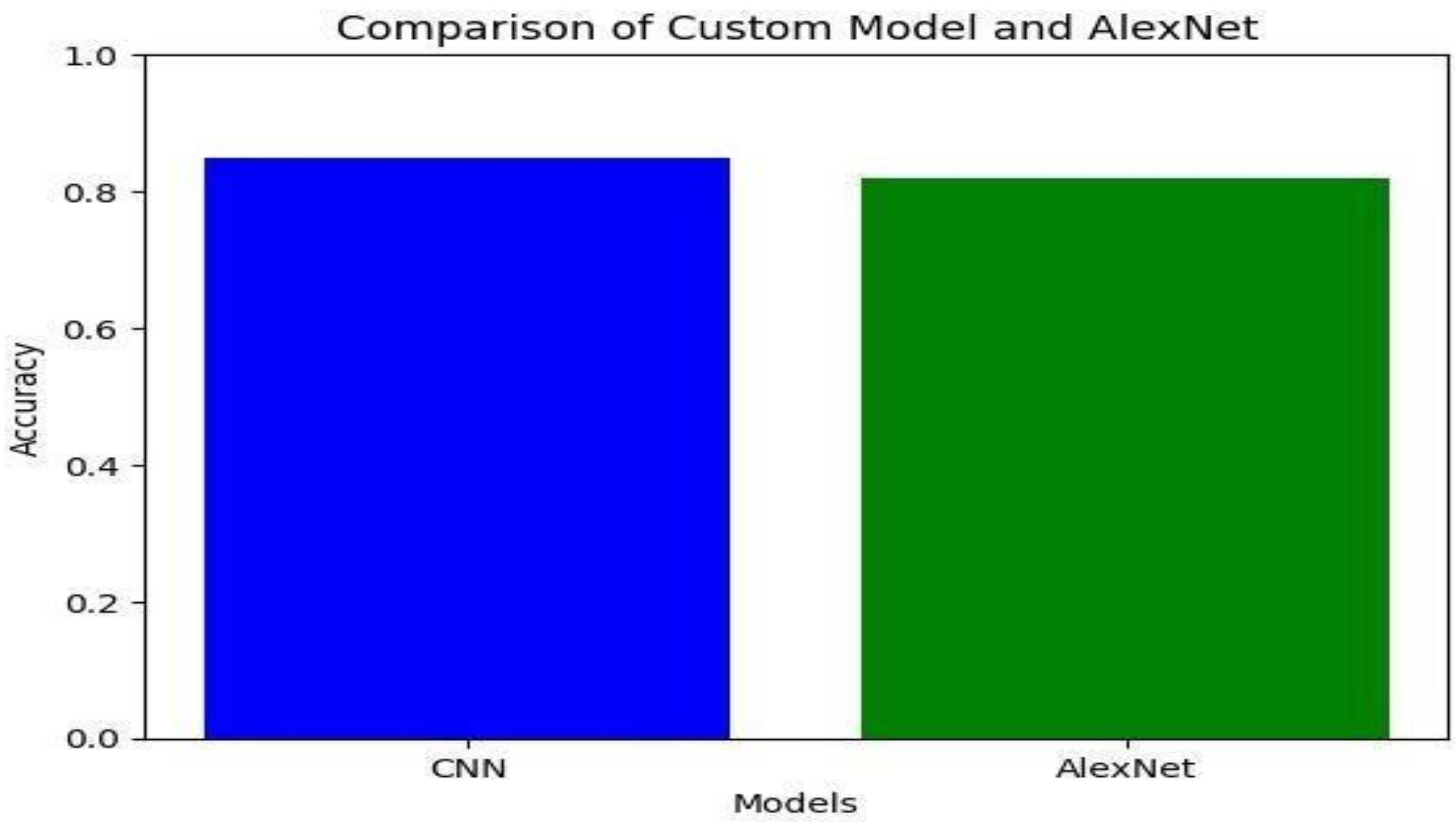
Classification Report :

Classification Report:

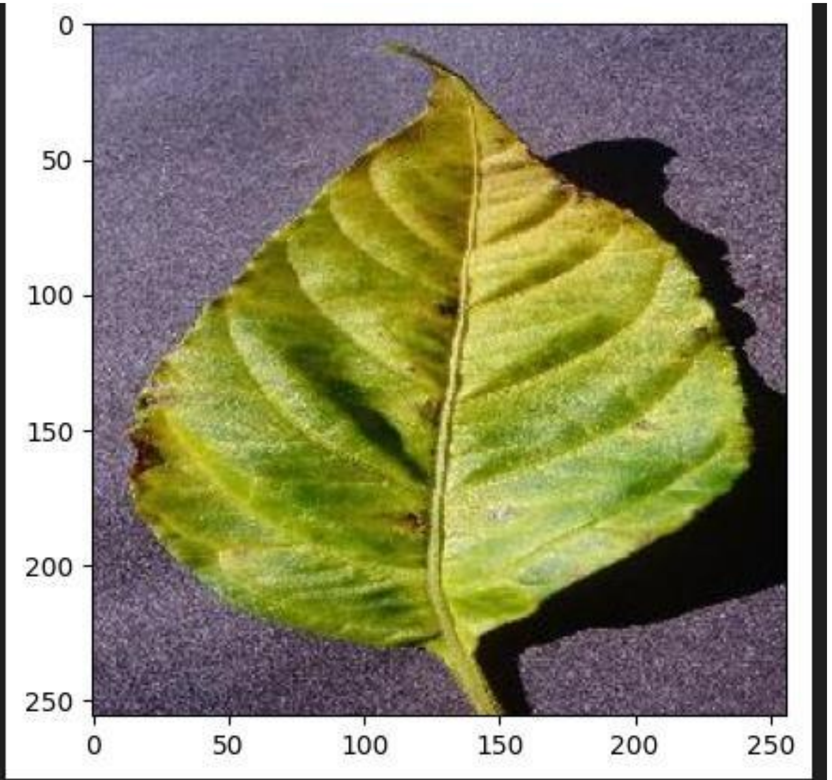
	precision	recall	f1-score	support
Pepper__bell___Bacterial_spot	0.00	0.00	0.00	199
Pepper__bell___healthy	0.04	0.06	0.05	295
PlantVillage	0.50	0.79	0.61	4127
Potato___Early_blight	0.03	0.17	0.05	200
Potato___Late_blight	0.00	0.00	0.00	200
Potato___healthy	0.00	0.00	0.00	30
Tomato_Bacterial_spot	0.00	0.00	0.00	425
Tomato_Early_blight	0.00	0.00	0.00	200
Tomato_Late_blight	0.00	0.00	0.00	381
Tomato_Leaf_Mold	0.00	0.00	0.00	190
Tomato_Septoria_leaf_spot	0.00	0.00	0.00	354
Tomato_Spider_mites_Two_spotted_spider_mite	0.00	0.00	0.00	335
Tomato__Target_Spot	0.00	0.00	0.00	280
Tomato__Tomato_YellowLeaf__Curl_Virus	0.00	0.00	0.00	641
Tomato__Tomato_mosaic_virus	0.00	0.00	0.00	74
Tomato_healthy	0.00	0.00	0.00	318
accuracy			0.40	8249
macro avg	0.04	0.06	0.04	8249
weighted avg	0.25	0.40	0.31	8249

Training VS Validation Accuracy




Comparison of Custom Model and AlexNet
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
CNN
AlexNet
Models

Output:




```
Predicted Class: Potato___Early_blight
```

Disscusion

- This project detects plant leaf diseases using the CNN deep learning model.
- The PlantVillage dataset with 15 disease categories was used. Images were resized, normalized, and split into training and validation sets.
- The model was trained for 3 epochs using early stopping and learning rate scheduling.
- Performance was evaluated using a accuracy/loss graphs.
- The model also successfully predicted new images, showing its practical use in smart agriculture.

Solution Impact

- The plant disease detection model provides a fast, cost-effective, and accurate method for identifying crop diseases using leaf images. By leveraging Custom CNN a lightweight deep learning model, the system can be deployed on mobile or edge devices, making it accessible to farmers in real-time. This can lead to:

- Early disease detection and reduced crop loss

- Improved yield and food quality

- Reduced reliance on expert diagnosis

- Support for smart agriculture and digital farming initiatives

- The Project code link : https://github.com/JayasriPoonkundran/Plant-Disease-Identification.git

Conclusion

- A deep learning-based system was developed to accurately detect 38 plant diseases using RGB images.
- Enables early detection, reduces need for experts, and minimizes crop loss.
- The tool is scalable, fast, and farmer-friendly, supporting sustainable agriculture.
- This AI solution bridges the gap between technology and traditional farming for better crop health and food security.

Future Scope

- **Mobile App & Edge Devices:** Deploy the model on smartphones, tablets, or drones for real-time, offline disease detection, making it accessible to farmers in remote areas.
- **Larger & Diverse Dataset:** Expand the dataset to include more crop species, regional diseases, and environmental conditions to improve model generalization and robustness.
- **Multimodal Diagnosis:** Integrate leaf images with data such as weather, soil quality, and crop history for a more comprehensive plant health analysis.
- **Early Detection & Severity Level:** Enable the model to detect diseases at early stages and assess severity levels, aiding in proactive and optimized treatment.
- **Integration with Smart Farming Tools:** Connect the system with farm management platforms, enabling automated decision-making and improving yield prediction and resource allocation.
- **Explainable AI:** Incorporate techniques to highlight affected areas on leaves, increasing user trust and helping farmers understand model predictions more effectively

Reference

1. **Rafique, M., & Jeon, G. (2020).** Plant disease detection using convolutional neural networks: A review. Journal of Electrical Engineering & Technology, 15(3), 1343-1355.

2. **Documentation. (2021).** Keras: Deep learning for Python.

3. **Szegedy, C., Vanhoucke, V., & Ioffe, S. (2016).** Rethinking the Inception Architecture for Computer Vision. Proceedings of the IEEE conference on computer vision and pattern recognition, 2818-2826.

4. **PlantVillage Dataset. (2020). Kaggle**: https://www.kaggle.com/datasets/emmarex/plantdisease

Appendix

1. Dataset Description

Dataset: PlantVillage
Number of Classes: 16

2. Model Architecture (Custom CNN)

Input Layer: 64X64 RGB images
Convolutional Layer 1 (ReLU, MaxPooling)
Convolutional Layer 2 (ReLU, MaxPooling)
Flatten Layer
Dense Layer
Output Layer with Softmax Activation

3.Metrics Used

Accuracy (built-in during training)
Precision, Recall, F1-Score (via classification_report)

4.Prediction Code Sample

```
img = image.load_img(img_path, target_size=(64, 64))
img_array = image.img_to_array(img) / 255.0
img_array = np.expand_dims(img_array, axis=0)
pred = model.predict(img_array)
predicted_class = class_labels[np.argmax(pred)]
```

5.Tools and Libraries

TensorFlow / Keras
NumPy
scikit-learn
Matplotlib (for graphs)