|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| S.No | Dataset | Model | accuracy | notebook |
| 1 | [All Plant Diseases Dataset](https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset) | CNN(same as 2 with different dataset)-90.8 | 94.04% | Leaf\_disease\_CNN\_vipool.ipynb |
| 2 | [All Plant Diseases Dataset](https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset) | CNN(different layers) | 94.04% | Leaf\_disease\_CNN\_new.ipynb |
| 3 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | CNN(same as 1 with different dataset) | 90.80% | Leaf\_disease\_CNN.ipynb |
| 4 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | CNN(with different layers) | 89.70% | Leaf\_disease\_CNN2.ipynb |
| 5 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | SVM | 84.00% | SVM.ipynb |
| 6 | [All Plant Diseases Dataset](https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset) | VGG16(modern CNN model) | 79.09% | vgg16.ipynb |
| 7 | [All Plant Diseases Dataset](https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset) | VGG19(modern CNN model) | 78.28% | leaf\_disease\_prediction.ipynb |
| 8 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | DenseNet(modern CNN model) | 71.80% | DenseNet121.ipynb |
| 8 | [All Plant Diseases Dataset](https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset) | GoogLeNet(modern CNN model) | 69.67% | Googlenet.ipynb |
| 10 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | ResNet(Modern CNN model) | 39.50% | ResNet.ipynb |
| 11 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | LeNet(basic CNN model) | 11.5% | LeNet.ipynb |
| 12 | [Tomato Leaf Disease Dataset](https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf) | i) RF  ii) Decision Tree | i) 10%  ii) 10% | leaf\_disease\_ML.ipynb |

The results presented in Chapter 4 showcase the performance of various models applied to different datasets for the task of plant disease classification. Let's delve into a detailed discussion of these findings:

**Comparison of CNN Models:**

The results demonstrate that using a CNN architecture (Model 2) with customized layers achieved the highest accuracy of 94.04% on the All Plant Diseases Dataset. This signifies the importance of model architecture in improving classification performance.

The CNN model applied to the Tomato Leaf Disease Dataset (Model 3) also showed competitive accuracy (90.80%), suggesting that the same model structure can generalize well across different plant disease datasets.

**Effectiveness of Transfer Learning:**

Transfer learning using pre-trained models like VGG16 and VGG19 (Models 6 and 7) yielded accuracies of around 79-78%, respectively, on the All Plant Diseases Dataset. Although these accuracies are lower compared to custom CNN architectures, transfer learning remains a viable approach for tasks with limited data or computational resources.

**Impact of Model Complexity:**

The DenseNet model (Model 8) achieved an accuracy of 71.80% on the Tomato Leaf Disease Dataset, which is notably lower compared to simpler CNN architectures. This suggests that while deeper and more complex models may offer certain advantages, they can also introduce challenges such as overfitting or increased computational requirements.

**Performance Variation Across Datasets:**

It's evident from the results that model performance varies significantly depending on the dataset. For instance, the ResNet model (Model 10) performed poorly with an accuracy of 39.50% on the Tomato Leaf Disease Dataset compared to other models, highlighting the importance of dataset characteristics in model selection.

**Exploring Non-CNN Methods:**

The SVM model (Model 5) achieved an accuracy of 84.00% on the Tomato Leaf Disease Dataset. While this accuracy is lower compared to CNN models, it indicates that traditional machine learning methods can still be effective for certain classification tasks.

**Challenges with Basic Models:**

Basic CNN models like LeNet (Model 11) exhibited very low accuracy (11.5%), emphasizing that more sophisticated architectures are generally required for accurate plant disease classification.

**Limitations and Future Directions:**

The results suggest several avenues for future research. These include exploring ensemble methods, improving data augmentation techniques, and investigating hybrid approaches combining CNNs with traditional machine learning algorithms to enhance classification performance and robustness.