TREE BARK IMAGE CLASSIFICATION FOR SPECIES IDENTIFICATION

Identification of tree species is crucial for various forestry-related tasks, including forest conservation, disease diagnosis and plant production. Bark, being a persistent feature regardless of seasonal variations, play pivotal role in providing a distinct identity to trees through structural variations. This project introduces a deep learning approach, utilizing computer vision techniques, to classify 14 tree species based on bark texture. The chosen methodology involves implementing a Convolutional Neural Network (CNN), specifically VGG16, employing a transfer-learning technique known as fine-tuning to enhance the model's performance. By using the advanced techniques, the model aims to achieve accurate and efficient classification of tree species.

Dataset:

Link: https://www.kaggle.com/datasets/saurabhshahane/barkvn50

The dataset used for the tree bark image classification project comprise a total of 14 distinct tree species. Each species is represented by a varied number of samples, with the class distribution detailed as follows:

- Adenium species:144 samples
- Anacardium occidentale:239 samples
- Artocarpus heterophyllus:138 samples
- Carica papaya:207 samples
- Chrysophyllum cainino:111 samples
- Cocos nucifera:110 samples
- Dipterocarpus alatus:158 samples
- Eucalyptus:127 samples
- Ficus microcarpa:150 samples
- Ficus racemosa:117 samples
- Musa:132 samples
- Psidium guajava:122 samples
- Terminalia catappa:113 samples
- Veitchia merrilli:152 samples

Data Visualization:

- To gain visual understanding of the class distribution, a bar plot has been generated.
- A subset of images has been visualized using 3x3 grid. Each image is associated with its corresponding tree species, allowing for a glimpse into the diversity of bark textures present in the dataset.

Data Augmentation and Model Splitting:

- Various augmentation techniques like rotation, width and height shifts, zooming, horizontal flipping etc. have been employed for enhancing the diversity of the training dataset to improve model generalization.
- The dataset is split into training and validation sets using a validation split of 0.1 (10% of the data is reserved for validation).

Model Training:

- Utilized a pre-trained a VGG16 model with ImageNet weight as base model for transfer learning.

- Froze the layers of the VGG16 base model to retain learned features during training.
- Constructed a custom classification head including a flattening layer and a dense layer with ReLU activation.
- Applied dropout regularization to mitigate potential overfitting issues.
- Compiled the model using the Adam optimizer and categorical cross-entropy loss.

Stratified K-fold Cross Validation:

- Performs 5-fold cross validation, iterating over different train-validation splits.
- For each fold, trains the model, evaluates it on the validation set, and prints the validation accuracy.

Model Evaluation:

- Overall accuracy of the model is 0.95, indicating that the model correctly predicted the class for 95% of the samples in the dataset.
- Precision = 0.95, Recall = 0.94, F1-Score = 0.94