**NATIONAL UNIVERSITY OF COMPUTER AND EMERGING SCIENCES-FAST**

**KARACHI CAMPUS**



**AI4002-Computer Vision**

**TITLE: Classification of plant Images**

**SUBMITTED BY:**

**20K-1712(Zain Vohra)**

**20K-0198(Hamza Tariq)**

**20K-1736(Ahmed Umer )**

**SECTION: BAI-7A**

**1. Introduction**

This report documents the development and evaluation of a model involving the classification of plant images into healthy and unhealthy categories. The dataset consists of images from healthy and unhealthy plants, and the goal is to build a robust model capable of accurate classification.

**1.1 Objectives**

* **Image Classification:** Develop a model capable of classifying plant images into two categories: healthy and unhealthy.
* **Data Exploration:** Understand the characteristics of the dataset, visualize sample images, and create a structured representation (CSV) of the data.
* **Data Preprocessing:** Standardize the image size, handle aspect ratio variations, and apply data augmentation techniques to enhance the model's ability to generalize.
* **Model Selection and Training:** Utilize pre-trained convolutional neural network (CNN) models, including VGG16, InceptionV3, Efficient Net, and ResNet50. Train these models on the dataset, monitor for overfitting, and employ techniques like dropout and early stopping.
* **Ensemble Learning:** Combine predictions from multiple models using an ensemble approach to improve overall classification accuracy.
* **Model Evaluation:** Assess model performance using metrics such as accuracy, precision, recall, and F1 score on a validation set.
* **Generalization Testing:** Evaluate the models, individually and as an ensemble, on new images to ensure their ability to generalize beyond the training set.

**2. Dataset**

**2.1 Data Collection**

The dataset comprises images of plants, specifically categorized into two classes: "Healthy Plant" and "Unhealthy Plant." Each class represents a different state of plant health. The images are likely to be in JPG or PNG format based on the code provided.

**2.2 Data Preprocessing**

The dataset was loaded and visualized using the OpenCV library. A CSV file was created to handle image paths and their corresponding labels (healthy or unhealthy). Images were preprocessed to ensure uniformity in size (224x224 pixels) and aspect ratio. Images were annotated according to their respective labels. Data augmentation techniques, such as rotation, shifting, and zooming, were applied to increase the model's robustness.

**3. Methodology**

**3.1 CNN Model Exploration**

Four pre-trained convolutional neural network (CNN) models were explored:

* VGG16
* InceptionV3
* Efficient Net
* ResNet50

**3.2 Model Adaptation for Binary Classification**

Each CNN model was adapted for binary classification by incorporating the following modifications:

* Addition of Dense Layers
* Integration of Dropout for Regularization

**3.3 Training Process**

* Training was executed on a designated training set.
* Data augmentation techniques were applied to enhance model generalization.
* Early stopping was implemented to prevent overfitting.

**4. Model Evaluation**

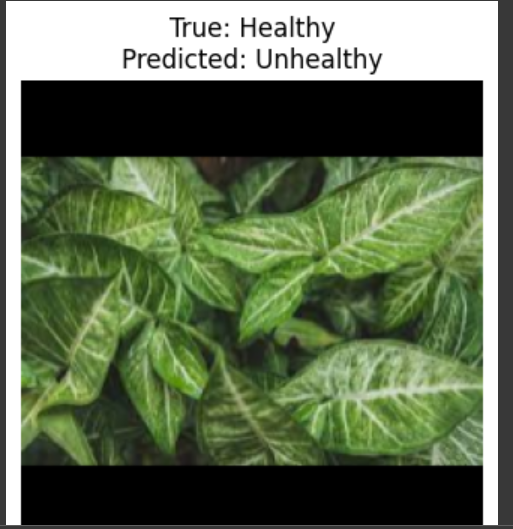
The first model we prepared was VGG16 which underwent evaluation on a dedicated validation set, with the following performance metrics computed:

* Accuracy
* Precision
* Recall
* F1 Score

Notably, VGG16 model achieved perfect scores on the validation set, demonstrating exceptional accuracy and generalization.



However, when given a test image, it was unable to predict correctly. Despite of using techniques like early callback and dropout, the model may have moved toward overfitting.



As a result, to enhance the model’s prediction capability, we introduced the ensemble approach.

**5. Ensemble Learning**

An ensemble approach was employed by combining predictions from individual models:

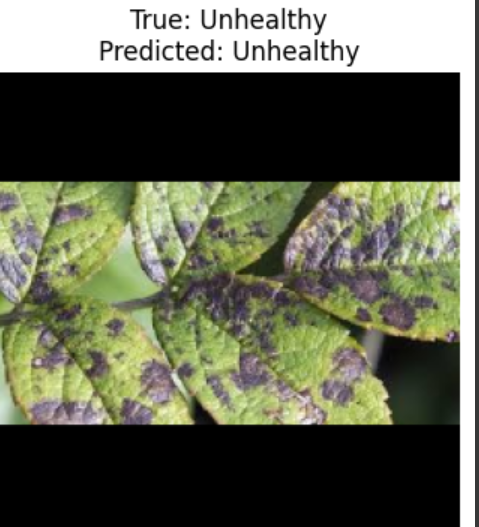
* VGG16
* InceptionV3
* Efficient Net
* ResNet50

The ensemble achieved a perfect accuracy score on the validation set, indicating enhanced overall model performance.

**6. Testing on New Images**

The ensemble model was tested on new images to showcase its capability to generalize to unseen data:

* Predictions were made on new images.
* Ensemble accuracy on the new images was reported.



The decision of choosing ensemble approach was a success as now our model was able to predict the test image correctly.

**4. Results**

**4.1 Model Performance**

The accuracy and other relevant metrics for each algorithm are summarized below:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Algorithm | Accuracy | Precision | Recall | F1-score |
| VGG-16 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Inception V3 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Efficient Net | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| ResNet50 | 0.9948 | 1.0000 | 0.9896 | 0.9948 |
| Ensemble Learning | 1.0000 | - | - | - |

**Note:** For the ensemble, precision, recall, and F1-score are not applicable as it's based on combining predictions from individual models. Accuracy is the primary evaluation metric in this context.

**5. Conclusion**

In conclusion, the ensemble approach, combining predictions from multiple pre-trained models, proved effective in achieving high accuracy and robustness in classifying plant images. The models were successfully trained and evaluated, showcasing their ability to generalize to new, unseen data. This report provides a comprehensive overview of the entire process, from data preprocessing to model training, evaluation, and the final ensemble approach.

**THANK YOU**