**BANANA LEAF DISEASE DETECTION AND CLASSIFICATION**

**ABSTRACT**

Bananas are one of the most important crops in global food security and economic significance within tropical and subtropical countries. Nonetheless, diseases such as the Black Sigatoka, Fusarium wilt and Banana Bunchy Top Virus pose a big danger to yields and quality, resulting into a huge loss in economical returns. An important aspect of disease detection involves manual inspection that is time-consuming, expensive and incapable of handling large scale farming. To address these challenges, this research develops an automated system for banana leaf disease detection and classification utilizing ResNet50, which is a deep learning model trained on the ImageNet database.

The base layers of the ResNet50 model are frozen to preserve its effective feature extraction mechanism, and additional new layers are created to address banana leaf disease classification problems. The set of images is pre-processed as follows: All of these images are uniformly resized to 128 x 128 pixels to fit the model. Finally, the model is saved in the H5 file format which makes its deployment highly efficient.

The system attains high classification rates that enhances the classification of the healthy leaves and multi-disease types. As for other measures of effectiveness, accuracy, precision, recall, and F1-score of the suggested model are high. This work shows one of the advantages of artificial intelligence in agriculture, where the problem is solved through a method that is accurate, fast, and less costly than the other methods. Through using this technology in mobile or IoT manners, farmers will be in a position to act on diseases, minimize the losses and practice proper farming systems.

**OBJECTIVES**

This study aims that this paper will focus on creating an automatic classification system for banana leaf diseases using the ResNet50 model. There is a need to enhance the ResNet50 architecture for real-world implementation with focus on practicability, and more to the point, the feasibility of the network with regard to its practical applications should be considered by standardizing it and making it less expensive. This model should be integrated into IoT and mobile based platforms to facilitate real time monitoring and early intervention for disease.

**METHODOLOGIES**

**Dataset Preparation**

The dataset used in this research comprises images of banana leaves classified into three main categories which are Healthy Leaves means leaves without any symptoms of disease. Diseased Leaves means banana leaves affected with Black Sigatoka, Fusarium Wilt or other banana diseases and other Leaves with conditions not directly related to the primary diseases of interest in the study. Key attributes of the dataset include: Image Dimensions: All images were scaled down to 128 x 128 pixels and all face images were especially cropped in order to fit the ResNet50 model. Class Balance: To avoid the spectra bias of training, attempts were made to balance the number of samples in the categories. Augmentation Techniques: The techniques of data augmentation were used to enhance the variety and robustness of the system. Methods used for augmentation were rotation, flipping, scaling and brightness changes. The Preprocessing Steps are ⁠all images were resized to 128 x 128 and then scaled to have pixel values in the range of 0 to 1. ⁠Methods of augmentation were used to increase the amount of the available data and add variation. ⁠The dataset was split into training, validation, and testing subsets in a 70:20:10 ratio.

**Model Architecture**

The ResNet50 model was chosen for its feature extraction capability which was learned during pre-training while using the ImageNet dataset. ⁠ResNet50’s first layers were fixed for posing as feature extractors pre-trained on ImageNet. ⁠More fully connected layers were added for feature extraction after which a softmax layer was added for multi-class output. ⁠The model maps images of size 128×128×3 (Height, Width and color channel). through pre-training on ImageNet. Base Layers: The initial layers of ResNet50 were frozen to retain the learned feature representations from ImageNet. Custom Layers: Additional dense layers were added for feature processing, followed by a softmax output layer for multi-class classification. Input Shape:⁠ ⁠The model takes images with a shape of 128×128×3 (height, width, and color channels). Architectural Diagram: You should also add a simple visualization of how the input layer, ResNet50 base, the added layers, and the classification layer looks like.

**Training and Evaluation**

Training Process: Optimizer: Adam optimizer was used because of its self adaptive learning rate and smooth convergence. Loss Function: To counter multi-class classification problem, categorical cross-entropy was employed. Batch Size: Due to computational cost, it became reasonable to choose the batch size of 32 and increase training speed. Epochs: It was trained for 50 epochs to ensure enough training completed before applying early stopping to avoid overfitting. Learning Rate: The starting learning rate of 0.001 was then adjusted using a schedule based on the validation loss.

Evaluation Metrics: Accuracy: The percentage of the samples that has been classified accurately. Precision: The proportion of all positive predictions by the model that are actually true. Recall: The number of true positives, divided by the total number of actual positives. F1-Score: A mean of the precision and the recall. Confusion Matrix: Plotted the classification performance of all the categories.

**KEY FINDINGS**

For this research, a pre-trained ResNet50 model was used with the dataset from ImageNet to classify and detect diseases in banana leaves. The dataset was moderately augmented, and to fine-tune the model categorical cross entropy was employed. The final validation accuracy was 61.96% showing that although there is evidence of pattern recognition concerning banana leaf diseases by the model, there is still much improvement that has to be made. Below are the key observations: Training Performance: The training accuracy improved with each epoch right from epoch 1 to epoch 100, suggesting that the model was able to correctly learn features of the training data. The training loss continued to decline which indicated that the model was learning the data well and was reducing the loss function correctly. Validation Performance: The validation accuracy was 61.96% and captures the level of ability of the model when predicting on unseen data. The validation loss showed instability, especially in the later steps, which could indicate fitting to noise or overfitting to the validation set. These results validate the ability of the model to identify banana leaf diseases, however, suggest that the data quality and the structure of the model as well as training processes can be further enhanced.

**IMPLEMENTATION STEPS**

Step 1:⁠Reduced the size of the images to 128 by 128. ⁠Normalized pixel values to the range of 0 to 1.⁠Diversified the dataset. ⁠The ResNet50 base was chosen, whereas only the additional layers were trained. ⁠Training data was passed to the model using the batch size of 32 until 50 epoch was completed.⁠ ⁠The trained model with weights and the state of optimizer was saved in an H5 file for the purpose of the deployment the range [0, 1]. ⁠Augmented the dataset for diversity.

Step 2: Model Training: ⁠The ResNet50 base was fine-tuned, training only the additional layers. ⁠Training data was fed into the model using a batch size of 32 for up to 50 epochs.

Step 3: Model Saving :⁠The trained model, along with weights and optimizer states, was saved as an H5 file for deployment. To ensure replicability, the following details are provided:

1.⁠ ⁠Data set features such as data augmentation and data preprocessing.

2.⁠ ⁠This work identifies ResNet50 neural network architecture and changes made in this study.

3.⁠ ⁠Learning rate, the type of optimizer, batch size and loss at the time of training.

4.⁠ ⁠Full code from data preparation to model building and testing and all intermediate steps.

To achieve this, the present study seeks to provide a detailed documentation of the employed methodology in the hope of promoting the enhancement and expansion of automated agriculture solutions and the domain of plant disease identification.

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