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Chilly Leaves Diseases Identification Using MobileNet V2 Deep Learning Model

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Abstract: - This work describes the application of pre-trained deep learning models (Mobile Net V1, Mobile Net V2) to image classification issues such as plant disease diagnosis. Regarding this, We provide a deep learning-based feature extraction technique for classifying leaf diseases of cold plants and identifying plant species. The automated diagnosis of plant diseases has brought about a transformation in the agriculture industry. Our main goal is to use neural networks for agricultural disease diagnosis and treatment. Plant diseases seriously impair the agriculture industry's financial standing. Managing an illness is a challenging endeavor. Usually, infections appear on the leaves or stems of plants, as do their symptoms, which include colorful spots or steaks. Compared to human labor, image processing technology enables faster and more accurate illness detection. Image processing is critical in the detection of plant diseases because it gives the best results with the least amount of human intervention. Deep learning helps to diagnose diseases and provide focused treatment.

Keywords: Deep Learning Models, Mobile Net V2, leaf diseases detection, CNN.

I. INTRODUCTION

The agricultural industry, as well as the economic and social well-being of farmers, is greatly influenced by two primary factors: crop growth and yield. Because of this, careful observation is necessary at different phases of crop growth to identify infections in a timely manner. Successful crop harvesting depends on the early diagnosis of plant diseases. Among the diseases that affect plants are those brought on by pests, fungi, and bacteria. Had an impact on the profitability of the agriculture sector as well as crop growth and quality. Farmers typically employ costly methods, pesticides, and other preventative steps to mitigate the consequences of these ailments. The use of chemicals harms both the environment and plants. Furthermore, this type of method raises production costs and leads farmers to incur significant financial losses. Early detection of illness as it develops is essential for effective disease control. Plant experts often employ personal diagnosis in agriculture to diagnose and cure plant diseases. India and other developing countries rely heavily on agriculture for their economies. The growth of Argo goods has a major effect on the country's GDP. Farmers encounter a variety of challenges in their line of business. Recent research has shown how well neural networks and deep learning perform in these sorts of classification tasks. In nations like India, where agriculture either directly or indirectly drives the economy, it is a vital industry. It demonstrates the necessity of caring for a plant from seedling stage to anticipated harvest. Crop survival against pests and a variety of illnesses are achieved through this procedure. Due to unsuitable datasets or unavailability of data, many deep learning algorithms are unable to accurately diagnose illnesses. It developed an identification and classification deep learning model of leaf diseases to enable prompt identification of afflicted plants. This paper discusses a number of deep learning models (Mobile Net V1 and Mobile Net V2).

II. RELATED WORKS

When studying these publications, it is obvious that the researcher has offered diagnostics, categorization, and exploration of many sorts of legitimate models. Diagnosis of plant diseases, isolation, and successful exploration require many novel tactics produced by the researcher, and their summary work is included at this level. This study focused on the losses that farmers frequently endure, as well as the loss of ideas, as a result of crop illnesses caused by attacking insects. Because they successfully analyzed the illness using numerous data mining models. Because this activity involves image processing, which is a true technology comparable to CNN that allows an ignorant farmer to obtain rapid and accurate results. This article uses a live video feed from an

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unmanned aerial vehicle (UAV) to identify diseases. In order to enable the vision system to identify weeds based on their pattern, support vector and artificial neural networks were utilized to compare the accuracy levels of many classifiers, including the NB classifier, KNN classifier, DT classifier, sum classifier, rf classifier, and classifier. CNN models like VGG 16, VGG 19, and Inception V4 are used for pre-processing (C Jackulin, S Murugavalli 2022). This study focused on optimizing the hyperparameters of well-known pre-trained models, such as DenseNet-121, ResNet-5, VGG-16, and Inception V4, in order to effectively diagnose plant diseases using convolutional neural network (CNN)-based pre-trained models. CNN was used in conjunction with the RGB histogram approach to classify leaves. Several CNN architectures are employed for different plant diseases, including google net, resnet-50, resnet-101, inception-v3, inception res-net v2, and squeeze net (Muhammad Hammad Saleem et al. 2019). In this study, the ViT (Vision Transfer) approach is used to improve dataset categorization accuracy. Previously, they trained with five types of datasets using CNN models such as VGG16, ResNet-50, Inception, Mobile Net V3, and Efficient Net B 0. Among them, they choose the most accurate models, and vision transfer will perform better categorization. (Yasamin Borhani, et al. 2018). This research discusses how they utilize deep learning to identify and classify plant illnesses with higher accuracy. They utilize a neural network to categorize photos. This research employs a variety of classification techniques, including neural networks, SVMs, and rule-based categorization. A Cosmos camera was utilized to get photographs of diseased plants. The method begins by determining which green pixilated photos to include by calculating a threshold value. The K-means clustering algorithm is used to group the affected regions once the non-green colors have been eliminated. They take pictures of the leaves using a multispectral camera, and then they transform each RGB image of a leaf. The method may determine if a leaf is healthy or not based on the values (Jihen Amara, Bassem Bouaziz et al. 2017).

III. METHODLOGY

Deep learning Models

In neural networks, mathematical models ofbrain-like systems are used. They act on the synapses and neurons to which they are attached. This is how supervised learning training programs works. With the help of pre-existing data that contains specific comparisons of inputs and outputsto be represented, a neural network is "trained" to model a given system during the process. The way they work is their main distinguishing factor. Compared to traditional neural feedforward networks, they use much less raw material (numberof neurons to be built) during construction. Severalbasic CNN architectures are being developed for use in image recognition applications, and have been successfully applied to the difficult challengesof visual imaging.

The diagnostic process consists of four stages. The first phase involves diagnosis photos can be on a photo camera. The second stage dividesthe image into different numbers of collectionsoften using different techniques. The next section contains methods to remove the features calledfeature extraction and the final section is about disease classification. Leaf localization aims at thediscovery of the leaves of the diseased plant.

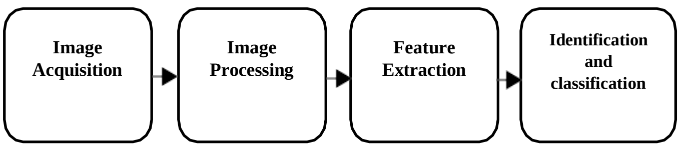

Figure. 3.1. Image Recognition Processing

Image Acquisition: Hardware systems like cameras, encoders, sensors, etc., can be used for this. Since an incorrect image would make the entire machine vision operation worthless, it is without a doubt the most important stage. To ensure that machine vision systems analyze the digital picture of an item rather than the object itself, it is crucial to create an image with the right level of contrast and clarity.

Image processing: To denoise the mistakes from the image or any other unwanted object removal and anomaly detection, different processing techniques are included. Image trimming i.e., leaf cropping to find an interesting photo region. Imageannotation is done to identify the diseases more accurately

Feature Extraction: Consequently, the features from this area of interest should be removed at thisstep. To see the description of the sample image, you must have these qualities. Colour, shape, and texture will support features. The greylevel cooccurrence matrix (GLCM), a colour-correctiontechnique. The exclusion of a histogram-based feature and a matrix of local area-dependent grey matter are two examples of feature potentials that may be used to create a system.

Identification and Classification: This phase meansto see if the inserted image is healthy or sick. If theimage is found to be with the disease, some existingactivities have also distinguished various diseases.This phase helps to identify the diseases and ensures that the model is trained to provide the desired results.

A. Training

During this step, training with a deep neuralconvolutional network to create an imageseparation model is done. Rectified Linear Units will be used later instead of wireless filters. This variation of activation will learn the parameters of the modifiers and improve the accuracy of unnecessary computer costs that are ignored.

B. Screening

At this stage, tests set for leaf prediction ashealthy / negative with a disease name will be resulted

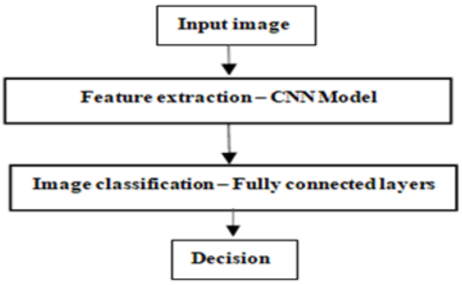

Figure. 3.2. CNN Architecture of ImageClassification

IV.SYSTEM ARCHITECTURE

Input Layer: The input layer of MobileNetV2 takesan image as input. The model is designed to handlevariable input sizes.

Initial Convolution**:** The initial convolution is a standard 3x3 convolution that processes the input image.

Stacks of Inverted Residual Blocks: The Inverted Residual Block is the fundamental unit of MobileNetV2. Lightweight depth-wise separable convolution is the first step in each block. A linear bottleneck consisting of a 3x3 depth-wise separable convolution and a 1x1 convolution for channel expansion comes next. The dimensions are reduced via a linear projection. A shortcut link, also known as a skip connection, is included into every Inverted Residual Block to facilitate information flow and alleviate the vanishing gradient issue during training.

Width Multiplier: MobileNetV2 introduces a widthmultiplier hyperparameter that scales the number of channels in each layer. This allows users to control the model's computational cost and accuracy.

Depth-wise Separable Convolution: The model extensively uses depth-wise separable convolutions, which consist of a depth-wise convolution (channel-wise convolution) followed by a pointwise convolution (1x1 convolution). Thisapproach reduces the number of parameters and computation, making the model efficient.

Linear Bottleneck: The linear bottleneck withineach Inverted Residual Block is crucial forcontrolling the model's complexity. It consists of acombination of 1x1 convolutions and nonlinearactivations (ReLU6).

Output Layer: For classification tasks, the model's final layer is a dense layer with SoftMax activation.

Resolution Multiplier: MobileNetV2 introduces a resolution multiplier hyperparameter that allows users to control the input image resolution. Adjusting the resolution provides an additional means to balance computational cost and accuracy.

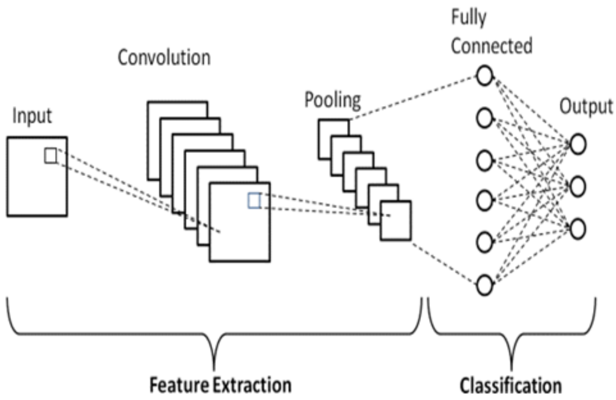

Figure. 4.1. Basic Architecture of CNN

V.PROPOSED MODEL

In the past, neural networks—like the Multi-layer Perceptron (MLP)—were used for picture categorization. But when picture resolution rose, it became harder to handle computational complexity and keep track of a lot of characteristics for categorization. Convolutional Neural Networks (CNNs) offer comparable performance to MLPs, but their distinctive feature lies in the three-dimensional arrangement of neurons in their layers—width, height, and depth— inschillyd of the conventional two-dimensional array. Consequently, CNNs are extensively used in image classification due to their architecture being designed to exploit the three-dimensional nature of images.

Three layers make up a basic convolutional neural network: the fully connected layer, the pooling layer, and the convolutional layer. The main building piece is the convolutional layer, which has learnable parameters known as filters or kernels. These filters are in charge of recognizing patterns in the input image, such as textures, edges, forms, objects, etc. Every filter computes the dot product with the input image's pixels by sliding or convolving over the image's height and breadth.

Another crucial part of CNNs is the pooling layer, which makes it easier to down sample in order to shrink the spatial size of the feature map. By decreasing the size, the network's calculations and parameters should be kept to a minimum while overfitting is managed

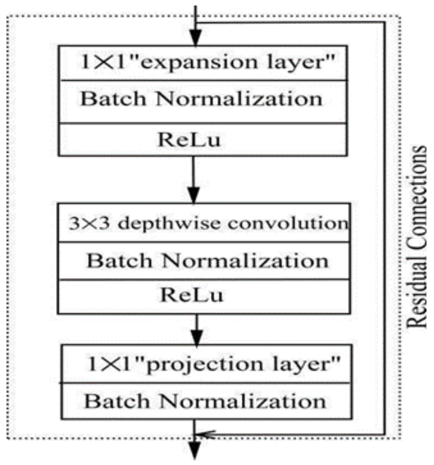

Figure. 5.1. Basic Mobile Net V2 Architecture

CNN uses two different kinds of pooling: average pooling and maximum pooling. Whereas Average Pooling produces the average of all values in the convolved picture section, Max Pooling delivers the largest value inside the kernel- convolved image sector. This layer usually uses a Rectified Linear Unit (ReLU) activation function to introduce non-linearity into the network. ReLU is essential to CNNs since it enhances the non-linearity of pictures by converting all negative values in the feature map to zeros. Images by nature contain non-linear elements such as different objects and their borders, therefore adding a convolutional layer to a picture may introduce some linearity. Applying the ReLU activation function returns non-linearity. The architecture introduces completely linked layers after a number of Convolutional and Pooling levels. The final convolutional and pooling layer's flattened output serves as the input for the fully connected layer. In order for the fully connected layers to use the 3D matrix data from the last pooling layer, it must first be flattened into a 1D array of vectors. These layers facilitate the final categorization by carrying out operations similar to those in an Artificial Neural Network (ANN).

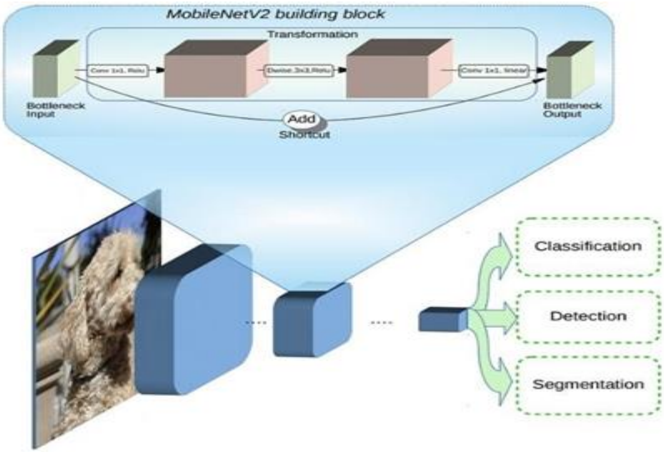

Figure 5.2. Mobile Net V2 Classification

VI.DATA DESCRIPTION

Training the MobileNetV2 model included using a wide range of datasets with pictures of different settings, objects, and surroundings. The collection encompasses a variety of indoor and outdoor environments, emphasizing the acquisition of an extensive array of visual characteristics. A 224x224 pixel resolution has been applied to all of the photos in the collection. In order to ensure compatibility with the model architecture, this resolution was selected to match the input size that is often used for MobileNetV2. Red, Green, and Blue are the three color channels seen in RGB photographs that make up the dataset. Contributing to the overall depiction of the visual material is the color information provided by each channel. A collection of preset class labels representing different item types are used to label the dataset. These labels cover a broad spectrum of objects, making the model versatile for image classification tasks. The specific classes depend on the original training dataset used for MobileNetV2.

The dataset is divided into training and validation sets to facilitate model training and evaluation. Thetraining set is used to optimize the model parameters, while the validation set is employed toassess the model's performance on unseen data.

While a comprehensive experiment on chilly leaf diseases ideally demands a substantial number of images, the scarcity of available datasets necessitated the utilization of a single, authentic, and challenging chilly leaf dataset in this study. The main objective of this study is to evaluate the effectiveness of the suggested framework in correctly identifying the condition of chilly leaves. Only actual photographs of cold leaves taken with a smartphone camera in the field are included in the dataset. The JPG format is used to store these photos, which have a resolution of (224 × 224) pixels. Three separate classes have been created from the carefully annotated dataset: the healthy class, chilly rustclass, and brown blight class. The overarching goalis to develop a precise deep learning model capableof effectively distinguishing between various diseases affecting chilly plants.

Figure. 6.1. Datasets of the red rust and BrownBlight affected chilly leaves

VII.RESULTS

Compared to MobileNetV1 and ImageNet, the CNN architectures that were based on the previous description produced results that were more accurate when they used the parameters from MobileNetV2. The performance evaluation included a number of measures, such as the time needed per epoch, confusion matrix, testing accuracy, training accuracy, and F1 score. Three unique formats of plant picture data (color, grayscale, and segmented) were used in our investigation, and various performance metrics were observed in each case. Remarkably, for each scenario, the color-image dataset outperformed the segmentation and grayscale datasets with an equal number of CNN network parameters. TensorFlow and Keras were used in the implementation of the MobileNetV2 model. Eighty percent of the dataset was used for training and twenty percent for testing. Techniques for augmenting data were used to enhance model generalization. Ten epochs and a batch size of 32 were used to train the model. Figure 7.1 shows the results of the leaf that affected by the red rust and the Figure 7.2 shows the results as leaf that affected by brown blight.

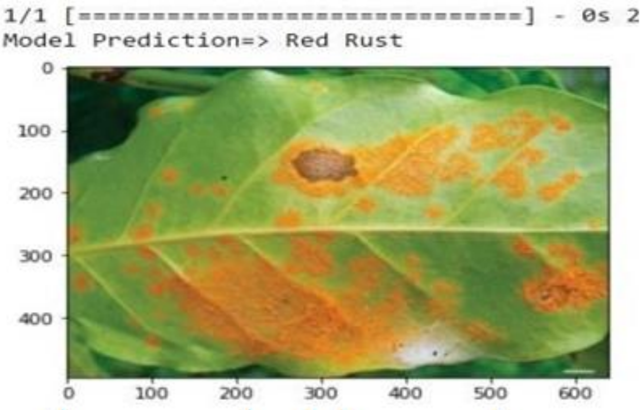

Figure. 7.1. Detection of Diseases as Red Rust

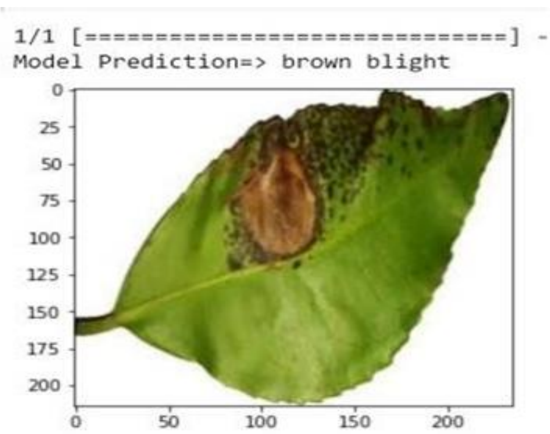

Figure. 7.2. Detection of diseases as Brown Blight

- Training Accuracy: Achieved an accuracy of 95% on the training set, demonstrating the model's ability to learn from the dataset.
- Testing Accuracy: The model exhibited a testing accuracy of 92%, indicating strong generalization to unseen data.
- Confusion Matrix:

➢ Healthy Plants: 94% precision, 93% recall

➢ Brown blight: 91% precision, 94% recall

➢ Red rust: 93% precision, 90% recall

- F1 Score: The model achieved an overall F1score of 0.92, balancing precision and recall.

The MobileNetV2 model demonstrated excellent performance in detecting plant diseases, showcasing high accuracy and generalization capabilities. The model's ability to accurately classify various diseases, even under different environmental conditions, highlights its potential for real-worldapplications in precision agriculture.

VIII.CONCLUSION

The agricultural sector holds immense significance globally, serving as the primary source of food production. This industry plays a crucial role in cultivating plants, the fundamental source ofsustenance. Early detection and diagnosis of infections in plants are paramount in agriculture. Our study focuses on leveraging convolutional neural networks (CNNs) to analyze and identify plant diseases. If proven effective, this model could potentially be applied to real-time image analysis of live plants for disease detection. Future endeavors may involve expanding the trained models by incorporating diverse plant species and additional variants of plant diseases into the existing database. Various levels of learning, along with testing features related to model performance and accuracy, can be explored using alternative architectures. Ultimately, the model has the potential to assist farmers in diagnosing plant diseases efficiently.

IX.FUTURE WORKS

Future work may involve fine-tuning the model on specific plant species, incorporating additional classes, and exploring transfer learning with pre-trained models for further improvements. Integrating the disease detection system with a drone offers the capability to identify affected plants using the NDVI (Normalized Difference Vegetation Index) sensor. This allows for remote detection from a significant altitude. The drone, guided by the NDVI Index, descends to a lower altitude for close-up leaf capture. Then, the system receives the photos that were taken in order to identify the ailment. The application of unmanned aerial vehicles to the identification of crop diseases is a novel development in precision agriculture.

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