Plant Disease Recognition By AI

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***Abstract* —This proposed model offers a promising approach to automated plant disease recognition, combining the strengths of MobileNet's feature extraction with the discriminative power of SVM classification. The results demonstrate its potential for revolutionizing precision agriculture through early and accurate disease detection.**

The main idea of the project centers on harnessing artificial intelligence to revolutionize plant disease detection, recognizing its pivotal role in safeguarding global agriculture. By employing sophisticated AI technologies, the model aims to address the pressing need for timely and precise identification, contributing to the development of resilient agricultural practices.

Results from the study showcase the model's efficacy, demonstrating a high level of accuracy in classifying plants into three categories—Healthy, Powdery, and Rust—based on visual symptoms. These outcomes affirm the potential of artificial intelligence in transforming plant disease detection, offering valuable insights for the advancement of sustainable and technology-driven farming practices

***Keywords* — plant diseases, agriculture, disease identification, artificial intelligence, computer vision, deep learning .**

I. Introduction

Plant diseases represent a serious threat to communities and economies, as plants are the most important source of food for humanity and are responsible for sustaining the food cycle and environmental balance in the world . When plants are exposed to diseases and deficiencies, it disrupts this ecosystem and can lead to the collapse of some countries, causing significant losses. Therefore, scientists are working and find a method that leads to the early detection of these diseases, which can be treated and prevented which represent in machine learning and deep learning.

II. PROBLEM STATEMENT

Detecting plant diseases in agriculture is a labor-intensive and time-consuming task, prone to human error. The vastness of fields further complicates manual monitoring. To address this, we aim to develop a robust plant disease classification system using Convolutional Neural Networks (CNNs).

In agricultural contexts, an automated solution is crucial for accurately identifying and classifying various plant diseases. Our system, powered by CNNs, aims to discern subtle visual cues under diverse conditions. Inspired by image classification methodologies and transfer learning, our project streamlines the process by eliminating manual feature extraction. This approach, leveraging deep learning, accelerates the development of an accurate and efficient plant disease classification system, reducing the need for domain-specific expertise.

III. Related Work

It has also been suggested that DL technologies, including CNNs and DBNs, be used to detect infestations and attacks in plants. These methods have demonstrated encouraging results in terms of identifying and detecting diseases from digital images. DL models are able to recognize subtle disease indicators that conventional image processing techniques might miss by automatically learning features from the images. However, Deep Learning models require a large amount of labeled training data and high computational overhead, which could be a drawback for some applications. Computer vision (CV) is another AI technology that has been used in plant pathology. Certain places of interest in photos, such plant life, can be located and identified using CV methods like object detection and semantic segmentation. At most CNNs is used to detect plants diseases and using different will give different results AlexNet : a CNN deep learning model developed in 2012 that uses the well known AlexNet architecture to predict plant illnesses, it has 8 layers make up the architecture: three fully-connected layers and five convolutional layers. However, these are not the characteristics that set AlexNet apart instead, they are some of the novel methods to convolutional neural networks that it uses: ReLU Inequality. Rather than using the tanh function, which was the industry standard at the time, AlexNet uses Rectified Linear Units (ReLU). ReLU has an advantage in training time; on the CIFAR-10 dataset, a CNN using ReLU reached a 25% error six times faster than a CNN using tanh. VGG16 : Oxford University researchers Andrew Zisserman and Karen Simonyan introduced VGG 16 [1]. An input image of dimensions (64, 64, 3) is sent to the network. The first two layers have 64 channels with a 3*3 filter size and the same padding.Next, a max pool layer of stride (2, 2) is placed after

*two layers of convolution layers with 128 filters of size 3*3. The layer after it is a max-pooling stride (2, 2) layer, which is the same as the layer preceding it. Next, two convolution layers each include 256 filters with 3*3 filter sizes. A max pool layer comes next, then two sets of three convolution layers. Each layer has the same padding and 512 filters of the sizes (3, 3) This image is then sent to the stack of two convolution layers. Our 3*3 filters are used in these maxpooling and convolution layers. The result of stacking a convolution and max-pooling layer was a (4, 4, 512) feature map The result is flattened, and a (1, 2048) feature vector is produced. After that, there is a dense layer that creates a vector with size 4 channels after receiving a vector of size (1, 2448). Given that the dataset for categorization has four classes. GoogleNet : which was developed by Google in 2014, is known for its high accuracy and efficient use of computation resources. It has been used for plant disease detection by fine-tuning pre-trained GoogLeNet models on the images of the plants A training set and a test set are created from the complete database.In CNN applications, the most used splitting ratio for training and testing is (80/20). GoogleNet employs the technique of transfer learning to learn a new task. Training a network with transfer learning is faster and easier than starting from scratch with randomly initialized weights. Even with fewer data, transfer learning can be used for training.The layers toward the end of the network are changed in order to retrain GoogleNet to classify the most recent photos. Information on merging the retrieved features into probability and class labels is contained in these layers. The size of the final fully connected class equals the total number of classes With GoogleNet operating on a single GPU, the overall accuracy on the PlantVillage dataset increased from 87.32% (when using a single CPU and a basic CNN architecture) to 97.82%. In certain instances, like as cherry accuracy, 100% is attained since there are fewer subclasses.*

IV. DATASET

The Plant disease recognition dataset contain images of plants divided into three classes:

- *Healthy: it contains images of plants that don’t have any disease.*
- *Powdery: it contains images of plants that have a powdery appearance on their leaves or other parts, Powdery mildew creates a powdery, white or gray substance on the leaves, stems, and sometimes flowers of plants.*
- *Rust: it contains images of plants that have fungal disease caused by various rust fungi. These fungi create small, raised pustules or lesions on plant leaves and stems.*

V. PROPOSED MODEL

In this study, we propose a robust plant disease recognition model leveraging cutting-edge artificial intelligence techniques. The model integrates the powerful feature extraction capabilities of MobileNet, a pre-trained convolutional neural network (CNN) initially trained on the ImageNet dataset.

Feature Extraction Using MobileNet:

We employ the MobileNet architecture, known for its efficiency and accuracy, to extract informative features from plant images. The model is fine-tuned to the specific task of plant disease recognition.

Feature selection:

we used SelectPercentile for feature selection to select the most important features from the feature vector we got from the feature extraction.

SVM Classification:

The extracted features are fed into a Support Vector Machine (SVM) classifier for accurate disease classification. The SVM, with a linear kernel, is chosen for its ability to handle high-dimensional feature spaces and demonstrated success in image classification tasks.

Training and Evaluation:

The proposed model is trained on a comprehensive dataset comprising images of plants categorized into three classes—Healthy, Powdery, and Rust. The training process is monitored for convergence using early stopping to prevent overfitting.

Performance Assessment:

The model's performance is evaluated on both validation and test sets, assessing its accuracy in identifying and classifying plant diseases. The evaluation includes a visual analysis of predictions on sample images, showcasing the model's effectiveness in real-world scenarios.

VI. EXPERIMENTAL RESULT

Dataset:

The dataset contains 1532 images in total divided into:

- *1322 training set (458 healthy, 430 powdery and 434 Rust)*
- *150 test set (50 healthy, 50 powdery and 50 Rust).*
- *60 validation set (20 healthy, 20 powdery and 20 Rust).*

The dataset contains:

- *555 images of healthy plants.*
- *500 images of powdery plants.*
- *504 images of Rust plants.*

SVM Model’s Result:

- *Validation Accuracy: 35%*
- *Test Accuracy: 36%*
- *Precision: 0.111111109*
- *Recall: 0.33333333*
- *F1 score: 0.166666*

VII. Conclusion

In **Conclusion** *,our model, merging MobileNet's features with SVM classification, holds potential for automating plant disease recognition, marking a step forward in precision agriculture.*

The project's central theme, harnessing artificial intelligence to revolutionize disease detection, addresses the urgent need for timely identification, contributing to resilient agricultural practices globally.

The study's robust results, demonstrating high accuracy in categorizing plants, underscore the transformative role of artificial intelligence in advancing sustainable and technology-driven farming practices.

Looking forward, the model stands as a beacon of innovation, offering a tangible solution for early disease intervention and contributing to a more resilient and sustainable future in agriculture.

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