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Disease Identification in Plants using Soft Computing Techniques

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ABSTRACT: The agricultural sector produces one of the most fundamental requirements to propagate the human species, i.e., food. We must mitigate any diseases that might pose significant challenges to the industry and the millions of people who are either directly or indirectly dependent on it for their livelihood. Pre-existing methods to identify these diseases are quite obsolete. In response, this project proposes a scientific approach that employs state-of-the-art soft computing technologies to bring about substantial improvements in the process, consequently resulting in a reliable method with improved accuracy and a healthier crop yield. The key to our Methodology is by leveraging deep learning mechanisms. Our proposed model utilizes Convolutional neural networks [CNNs], feature extraction, normalization techniques, and many more soft computing techniques to intricately analyses images of plant leaves and extract protruding features/patterns that are indicative of various diseases. Through extensive training and optimization, we aim to improve the efficacy of our model substantially over time.

KEY WORDS: Plant Disease, Neural Network, Smartphone application, Accuracy

I.INTRODUCTION

The health of plants is essential for sustaining agriculture, which in turn supports global food security, economies, and ecosystems to thrive and flourish. Traditional methods in this regard, although have undeniably been quite effective, are still very time-consuming, labor-intensive, and prone to human error. Furthermore, the reliance on expert knowledge. Limits the scalability of disease diagnosis, notably in regions lacking sufficient agricultural expertise. Using neural network models for identifying plant diseases can significantly enhance the precision and efficiency of detecting diseases in agriculture. Early and accurate detection is essential for implementing effective management strategies, reducing crop losses, and maintaining high productivity in farming. This advancement can assist farmers in making well-informed decisions about disease management, such as timely pesticide application or removing infected plants. In regions with limited access to agricultural experts, AI-based diagnostic tools can be particularly beneficial, promoting more sustainable farming practices. Ultimately, improving plant disease detection with neural networks can lead to increased food security, economic stability, and environmental sustainability by reducing the reliance on chemical treatments and fostering healthier crops.

II. LITERATURE REVIEW

This survey section is to examine the current development in the field of Deep Learning and the use of soft computing for plant disease detection. We have covered papers from the past decade that make use of concepts like machine learning and neural networks to detect and diagnose diseased plants from images. Thorough research was conducted through publications within the last ten years using databases such as Google Scholar and IEEE Xplore, with importance placed on relevance and citations received on the paper.
It is well known that chlorophyll is the pigment present in leaves which is responsible for their green color, and a deficiency of chlorophyll is responsible for the change in the color of the leaves . Greener leaves indicate that the crop is healthy and will result in a higher yield. Thus, in any form of disease detection in plants, we must judge how green the leaves are. Any discoloration or blemishes on the leaves are a good indicator that the plant is diseased.

Soft computing methods have seen a rise in popularity in many different sectors and agriculture is one such important sector. The use of these methods has seen a sharp rise in popularity in recent years and reviews have been conducted to identify suitable models in the agricultural sector. A method used in the perpetual quest for the most accurate and optimized machine learning technique for plant disease detection was Random forests. Overfitting is a common problem faced by decision trees and Random forests were shown to be a better model. Ramesh et al. in used various machine learning models for the identification of diseases in papaya leaves but was only able to obtain a maximum accuracy of 70.14% in their study using Random forests.

Sachin D. Khirade et al. in used image processing to accurately diagnose plant diseases. They considered five main steps to detect and diagnose diseases namely Image Acquisition, Image pre-processing, Image segmentation, feature extraction and detection and classification of the plant disease. Since the greenness of leaves is an indicator of plant health, color, along with texture and morphology was used in feature extraction to give accurate results. The differentiation of the diseased region from healthy regions is an important feature in assessing the severity of the disease and Sachin D. Khirade et al. used Self-Organizing Feature Map (SOFM) to achieve this. The use of ANN methods was found optimal in the classification of plant diseases from a given data set.

So, the question that arose was which soft computing technique is most suited for use in plant disease detection. A review conducted by Mrs. Shruthi U et al. found that when comparing different models such as Support Vector Machine (SVM) Classification Technique, Artificial Neural Network (ANN) Classification Technique, K- Nearest Neighbor Classification Technique, Fuzzy C-Means Classifier and Convolutional Neural Network Classification methods, CNN proved to have detected the most diseases and achieved the highest accuracy. A lot of work has hence gone into using CNN for image classification purposes. Kawasaki et all used the concept of CNNs to identify diseases in cucumber leaves. They have effectively distinguished between the melon yellow spot virus, the zucchini yellow mosaic virus, and a healthy plant with an accuracy of 94.9%. Using CNN, Lu et al. were able to identify 10 common rice-based diseases.

The need now arose to deliver these models in a commonly available package that was available to all. A smartphone-based application is an easy and accessible method to implement the studies carried out based on using soft computing techniques to detect plant diseases. Andrianto et al. developed a smartphone-based application for the detection of rice plant diseases. They developed a cloud server-based application that uses the phone’s camera to capture images of the diseased plant and uploads it to the server that performs the plant disease predictions and sends back a response. It was found that using the VGG16 CNN architecture gave a train accuracy value of 100% but a test accuracy value of only 60%, showing that higher accuracies in smartphone-based applications are indeed possible.

III. METHODOLOGY AND IMPLEMENTATION

The dataset used for training is called “New Plant Disease”. The dataset contains the following plants and their corresponding diseases;

Plant Species:

1. Apple
2. Blueberry
3. Cherry
4. Corn (Maize)
5. Grape
6. Orange
7. Peach
8. Pepper
9. Potato
10. Raspberry
11. Rice
12. Soybean
13. Squash (Cucurbita)
14. Strawberry
15. Tomato
16. Wheat

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Diseases:
1. Apple: Scab, Black Rot, Rust
2. Cherry: Powdery Mildew
3. Corn (Maize): Northern Blight
4. Grape: Black Rot, Esca, Blight
5. Peach: Bacterial Spot
6. Pepper: Bacterial Spot
7. Potato: Early Blight, Late Blight
8. Squash (Cucurbita): Powdery Mildew
9. Strawberry: Scorch
10. Tomato: Bacterial Spot, Early Blight, Late Blight, Mold, septoria Spot, Spider Mites, Mosaic Virus, Curl Virus
11. Orange: Greening.
12. Rice: Brown Spot, Leaf Blast, Neck Blast.
13. Wheat: Brown Rust, Yellow Rust.

A. Dataset Preparation:

The dataset for this project was collected from a variety of sources, including agricultural centers and online repositories dedicated to providing large and comprehensive information. To ensure the highest quality of data, each image was meticulously annotated with labels corresponding to the specific plant species and disease condition it depicted. This annotation process was rigorous, involving multiple rounds of verification to guarantee accuracy and consistency in the process of training the neural network model.

B. Dataset Splitting:

The dataset is divided into training and validation sets in an 80/20 ratio to facilitate model training and evaluation. This split is performed in a manner that preserves the directory structure, ensuring that the distribution of classes remains consistent between the training and validation datasets. This approach helps in maintaining the integrity of class distributions, which is crucial for the reliable performance assessment of the model.

C. Dataset Pre-processing:

The preprocessing pipeline was implemented using Python, leveraging the capabilities of the OpenCV library to handle image augmentation and normalization tasks. This pipeline was automated to streamline the preprocessing steps, ensuring that all images underwent consistent transformations. Data augmentation techniques such as rotation, flipping, zooming, shifting, and shearing were applied to induce a certain discernible amount of variability of the training set. Normalization on the other hand scaled pixel values to a standard range, i.e. [0,1] representing standard deviation and mean, respectively, in order to facilitate a faster and more effective model training. The techniques are intricately presented and explained in the sections below.

D. Dataset Augmentation:

Data augmentation is employed to increase the variability of the training set, which aids in enhancing the model's generalization ability. The following augmentation techniques are applied:

- Rotation: Images are rotated randomly within a specified degree range to introduce variability.
- Horizontal and Vertical Flipping: Images are flipped horizontally and vertically to create mirror images, thereby increasing the dataset size.
- Shifting: Images are shifted horizontally and vertically to vary their positions within the frame.

These augmentation techniques help make the model prepared for various transformations, thereby improving its performance on unseen data.

E. Normalization:

Normalization is performed to scale pixel values to a standard range, typically [0,1]. This step is crucial as it helps in faster convergence of the neural network during training. Additionally, the images are resized to a standard size required by the neural network models to ensure uniformity across the dataset. Normalization not only accelerates the training process but also contributes to more stable and efficient model learning.

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By implementing these preprocessing steps, the dataset is prepared in a manner that maximizes the model's ability to learn and generalize from the data, ultimately leading to better performance in plant disease classification.

F. Hyperparameter Tuning:

Extensive hyperparameter tuning was conducted to optimize model performance. Experiments were carried out with various learning rates, batch sizes, and epochs. Some techniques were employed to systematically explore the hyperparameter space and identify the best configurations for the models.

1. Learning Rate: Initially set to 0.001 with a set decay schedule.
2. Batch size: 32
3. Epochs: 10-15, chosen to balance training time and model performance.
4. Optimizer: Adam, chosen for its efficient handling of sparse gradients.

G. Training Environment

The training process leveraged high-performance GPUs, Particularly the Nvidia RTX 3060 to accelerate the computationally intensive tasks. This setup allowed for seamless management and dissemination of resources, ensuring that the training process could handle the large dataset and complex models effectively.

1. Hardware: Models are trained using the Nvidia RTX 3060 GPU to facilitate the training process due to the complexities involved.
2. Software: TensorFlow and Keras frameworks are used for model implementation and training.

H. Deployment and Integration

Following the training and evaluation phases, the trained models were integrated into an android application. This integration enabled seamless interaction between the models and the end-users, providing real-time disease identification capabilities. This was done with an objective of a seamless incorporation into the existing agricultural ecosystem, enhancing their utility and accessibility for farmers and agricultural experts.

I. User Interface Design

A user-friendly interface was designed for the mobile application, prioritizing ease of use and accessibility. The interface included features for real-time disease identification, allowing users to quickly and accurately diagnose plant health issues.

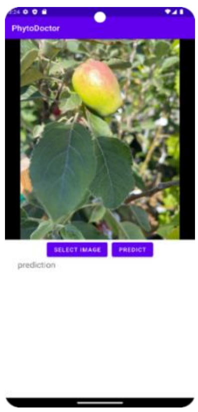

Fig 3.1: App Layout

IV. RESULTS AND DISCUSSIONS

The MobileNet model, designed based on Convolutional Neural Network (CNN) architecture, was trained and evaluated over a course of 10 epochs. The following metrics summarize the performance of the model:

1. Training Accuracy: The model achieved an average training accuracy of 96.26% across the 10 epochs.

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2. Testing Accuracy: The model maintained a high level of accuracy on unseen data, achieving a testing accuracy of 96.02%.
3. Training Time: The average time taken for each epoch was 45 minutes. This consistent training time per epoch reflects the efficiency of our training setup and resource utilization.

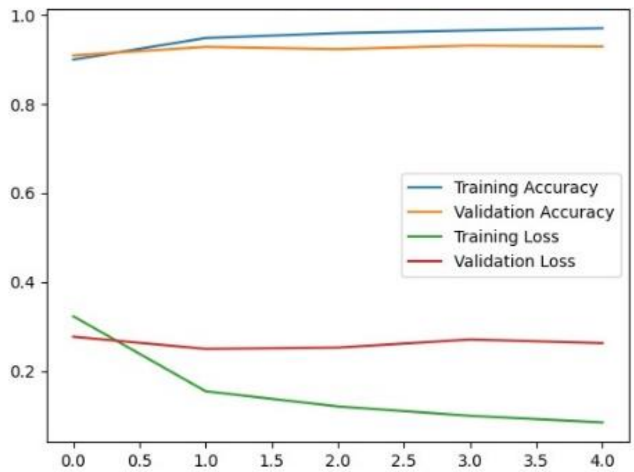

Fig4.1: Accuracy Curve

Listed below are the illustrations of our model accurately predicting whether the leaf is diseased or not, and specifying the disease if it is diseased.

Fig4.2: Diseased Leaf

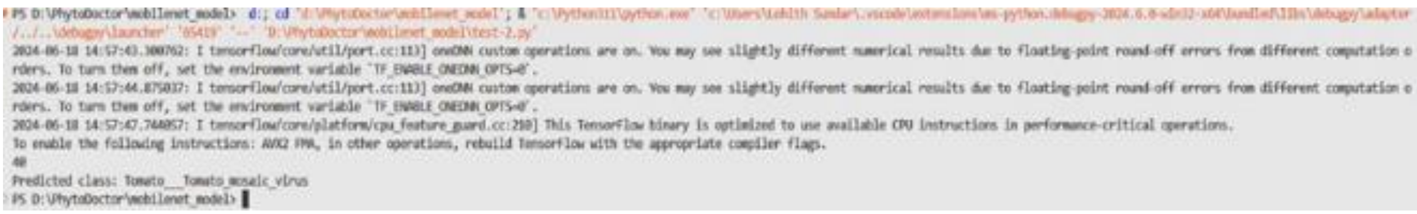

Fig4.3: Model Prediction

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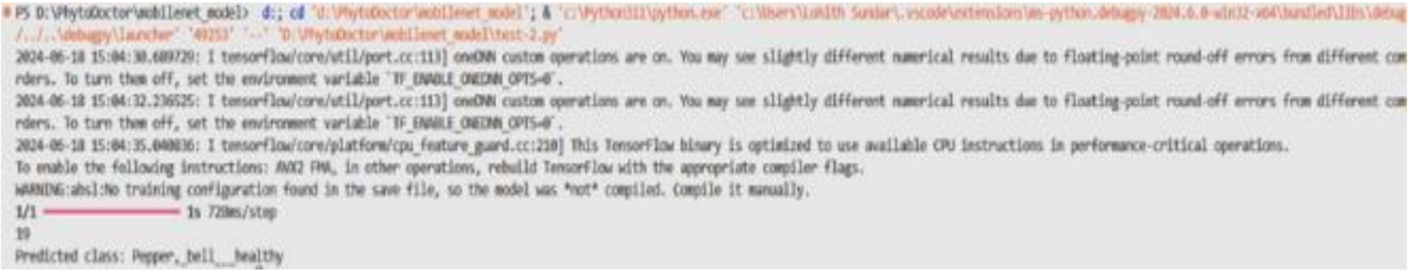
Fig4.4: Healthy Leaf



```
PS D:\PhytoDoctor\mobilenet_model> d:; cd 'd:\PhytoDoctor\mobilenet_model'; & 'c:\Python311\python.exe' 'c:\Users\Lohith Sundar\.vscode\extensions\ms-python.debugpy-2024.6.0-win32-x64\bundled\libs\debug
/../..\debugpy\launcher' '49253' '--' 'D:\PhytoDoctor\mobilenet_model\test-2.py'
2024-06-18 15:04:30.689729: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different com
rders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-06-18 15:04:32.236525: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different com
rders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-06-18 15:04:35.040836: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
WARNING:absl:No training configuration found in the save file, so the model was *not* compiled. Compile it manually.
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 728ms/step
19
Predicted class: Pepper,_bell___healthy
```

Fig4.5: Model Prediction

In addition to developing the MobileNet model, we successfully designed and integrated the model with a mobile application. This application allows users to leverage the capabilities of the model in a practical, user-friendly manner.

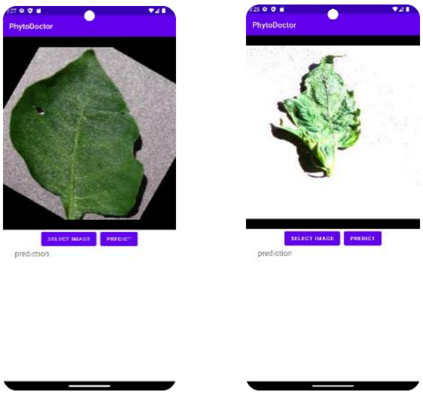


Fig4.6: Smartphone Application Overview

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V. CONCLUSION

Neural network-based plant disease detection systems could improve their effectiveness, scalability, and usability. Model generality will be improved by expanding datasets to encompass a wider range of plant species and illnesses, as well as including real-time data collecting via drones and IoT devices. Crowdsourced data from farmers can help to diversity the dataset. Advanced preprocessing approaches and automated picture augmentation can help improve feature extraction accuracy. Implementing edge computing for real-time detection, interfacing with farming equipment, and delivering automated treatment recommendations will improve field efficiency. The system will be improved through continuous learning, user feedback, and collaboration with agronomists and agricultural groups. Ensuring data protection, accessibility, and ethical considerations will help to drive acceptance and development, making the system an invaluable instrument for sustainable agriculture.

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