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Handling Severity Levels of Multiple Co-Occurring Cotton Plant Diseases Using Improved Mobilenet

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ABSTRACT

This study presents an enhanced MobileNet-based system for detecting multiple co-occurring cotton leaf diseases and assessing their severity. The lightweight architecture, optimized with skip connections and an αIoU-based loss function, ensures fast and accurate inference on mobile and drone platforms. An integrated image processing pipeline performs grayscale conversion, noise filtering, segmentation, and contour detection to isolate infected regions. Based on disease type and severity, the system recommends suitable fertilizers to aid targeted crop treatment. A dataset of 2,000 locally collected leaf images was used for evaluation. The proposed model achieved 98% mAP, outperforming baseline MobileNet and providing actionable insights for farmers.

Keywords: Cotton Diseases, MobileNet, Deep Learning, Severity Detection, Image Classification, Plant Health, Disease Diagnosis, Smart Farming, Real-Time Detection, Agricultural AI. Ask ChatGPT

I.INTRODUCTION

Cotton is one of the most important cash crops globally, serving as a primary source of natural fiber for the textile industry. However, cotton cultivation is frequently threatened by various plant diseases, which significantly affect yield and quality. These diseases often co-occur, making it difficult for farmers to identify and manage them effectively. Manual inspection is time-consuming, requires expert knowledge, and is prone to human error. In recent years, the use of artificial intelligence, particularly deep learning, has shown promising results in automating plant disease detection and classification. The challenge in cotton disease management lies not only in detecting the presence of disease but also in identifying multiple diseases that can appear simultaneously on a single plant. Moreover, understanding the severity level of each disease is essential for deciding the right type and timing of treatment. Traditional methods fail to handle this complexity effectively, leading to either under-treatment or overuse of pesticides, both of which are harmful to the crop and the environment. To address this problem, deep learning models, especially convolutional neural networks (CNNs), have been applied in agricultural image analysis tasks. Among these models, MobileNet stands out for its lightweight structure, making it suitable for real-time implementation on mobile devices and drones. However, the original MobileNet architecture may not fully capture the intricate patterns of multiple, overlapping disease symptoms with varying severity levels. In this project, an improved version of the MobileNet architecture is proposed to handle the detection and severity assessment of multiple co-occurring cotton diseases. This enhanced model incorporates fine-tuned layers and attention mechanisms to better focus on critical features within the leaf images. The goal is to build a model that is both accurate and efficient, suitable for deployment in real-world farming environments. A dataset consisting of cotton leaf images with multiple labeled disease types and severity levels was used for training and evaluation. The images were preprocessed to enhance clarity and consistency, and then augmented to improve the model's robustness. The improved MobileNet model was trained to classify each disease and assign a severity level, ranging from mild to severe, based on the visual symptoms present. Experimental results showed that the improved MobileNet outperformed the standard version and other baseline models in terms of classification accuracy, precision, recall, and F1-score. The model demonstrated strong performance even when multiple diseases were present in a single image. This shows its potential for accurate, multi-label classification, which is vital in practical agricultural scenarios where plants are rarely affected by just one disease at a time. The model's lightweight architecture ensures fast inference times, making it suitable for integration with smartphone applications or portable diagnostic tools. This allows farmers to quickly capture an image of the infected plant, receive instant disease identification and severity analysis, and take immediate action. Such real-time decision-making is key to minimizing crop losses and ensuring timely intervention. This system not only supports farmers in managing their crops more effectively but also contributes to sustainable agriculture. By accurately identifying the severity of diseases, it helps reduce unnecessary chemical usage, preserving soil health and reducing environmental pollution. It also lowers costs and enhances productivity, especially for small-scale farmers who lack access to expert guidance. Future work can explore extending this model to detect pests, nutritional deficiencies, and diseases in other crops, creating a comprehensive digital plant health monitoring system. Integration with Internet of Things (IoT) devices and satellite imaging can further enhance its capabilities and scalability. In conclusion, handling the severity levels of multiple co-occurring cotton plant diseases using an improved MobileNet model provides a practical and impactful solution for modern agriculture. It brings artificial intelligence into the hands of farmers, enabling smarter farming practices, higher crop quality, and a more resilient agricultural ecosystem.

II.RELATED WORKS

[1] Plant disease prediction using machine learning algorithms.

The proposed research work is for analysis of various machine algorithms applying on plant disease prediction. A plant shows some visible effects of disease, as a response to the pathogen. The visible features such as shape, size, dryness, wilting, are very helpful to recognize the plant condition. The research paper deals with all such features and apply various machine learning technologies to find out the output. The research work deals with decision tree, Naive Bayes theorem, artificial neural network and k-mean clustering and random forest algorithms. Disease development depends on three conditions-host plants susceptible to disease, favorable environment and viable pathogen. The presence of all three conditions is must for a disease to occur.

[2] Web enabled plant disease detection system for agricultural applications using wmsn

In this paper, a novel web enabled disease detection system (WEDDS) based on compressed sensing (CS) is proposed to detect and classify the diseases in leaves. Statistical based thresholding strategy is proposed for segmentation of the diseased leaf. CS measurements of the segmented leaf are uploaded to the cloud to reduce the storage complexity. At the monitoring site, the measurements are retrieved and the features are extracted from the reconstructed segmented image. The analysis and classification is done using support vector machine classifier. The performance of the proposed WEDDS has been evaluated in terms of accuracy and is compared with the existing techniques. The WEDDS was also evaluated experimentally using Raspberry pi 3 board.

[3] A Data Augmentation Method Based on Generative Adversarial Networks for Cotton Leaf Disease Identification

Focusing on the lack of training images of cotton leaf diseases, this paper proposes a novel model named Leaf GAN, which is based on generative adversarial networks (GANs), to generate images of four different cotton leaf diseases for training identification models. A generator model with degressive channels is first designed to generate cotton leaf disease images; then, the dense connectivity strategy and instance normalization are fused into an efficient discriminator to identify real and fake disease images by utilizing their excellent feature extraction capability on cotton leaf lesions.

[4] Cotton Leaf Spot Identification Under Limited Samples by Fine Grained- a fine grained-GAN

based cotton leaf spot identification method was proposed for local spot area image data augmentation to the generated local spot area images which were added and fed them into deep learning models for training to further strengthen the generalization ability of the classification models, which can effectively improve the accuracy and robustness of the prediction. Including 500 early-stage cotton leaf spot images every category were fed into the proposed fine grained-GAN for local spot area data augmentation, 1000 local spot area sub images every category were generated in this study.

[5]Plant disease prediction using machine learning algorithms.

The proposed method using the Enhanced VGG16 model with Faster Region-based Convolutional Neural Networks (R-MOBILENET) is compared with different networks, including VGG16, GoogLeNet, ResNet50, and AlexNet. The experimental results on the cotton leaf diseases demonstrated that the proposed method achieves the mean Average Precision) mAP (criterion improvements of 0.53%, 0.912%, 2.759%, and 7.268% compared with the ResNet50, VGG16, GoogLeNet, and AlexNet networks,

III.PROPOSED SYSTEM

The proposed system is designed For the cotton leaves disease identification task, MOBILENET architectures are employed. To complement the simplicity of our approach, we adopted two lightweight but efficient stateof-the-art pre-trained MOBILENET architectures, MobileNet. The adopted architectures have been trained on the ILSVRC-2012 ImageNet dataset (1k classes/1.3 million images). The transferable parameters of these models enable them to converge faster and yield better results. Overall, we utilized the aforementioned models off-the-self using their trained weights as the starting point and fine-tuned them on the PlantVillage dataset.

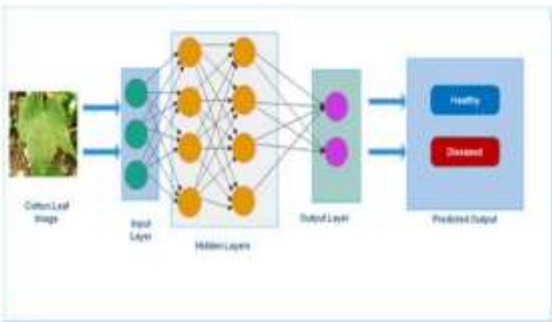

Figure 1: System Architecture of proposed system

IV. MODULES

- Dataset
- Retrieving the images
- Splitting the dataset
- Building the model
- Apply the model and plot the graphs for accuracy and loss
- Accuracy on test set
- Saving the Trained Model

Dataset

In the first module, we developed the system to get the input dataset for the training and testing purpose. We have taken the dataset from kaggle and some other out source.

The dataset consists of 20,081 Cotton Leaf Diseases images.

Retrieving the images

We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into numpy array.

Splitting the dataset

Split the dataset into train and test. 80% train data and 20% test data.

Building the model

The concept of convolutional neural networks. They are very successful in image recognition. The key part to understand, which distinguishes CNN from traditional neural networks, is the convolution operation. Having an image at the input, CNN scans it many times to look for certain features. This scanning (convolution) can be set with 2 main parameters: stride and padding type. As we see on below picture, process of the first convolution gives us a set of new frames, shown here in the second column (layer). Each frame contains an information about one feature and its presence in scanned image. Resulting frame will have larger values in places where a feature is strongly visible and lower values where there are no or little such features. Afterwards, the process is repeated for each of obtained frames for a chosen number of times. In this project I chose a classic MOBILENET and V3 model which contains only two convolution layers.

The latter layer we are convolving, the more high-level features are being searched. It works similarly to human perception. To give an example, below is a very descriptive picture with features which are searched on different CNN layers. As you can see, the application of this model is face recognition. You may ask how the model knows which features to seek. If you construct the CNN from the beginning, searched features are random. Then, during training process, weights between neurons are being adjusted and slowly CNN starts to find such features which enable to meet predefined goal, i.e. to recognize successfully images from the training set.

Between described layers there are also pooling (sub-sampling) operations which reduce dimensions of resulted frames. Furthermore, after each convolution we apply a non-linear function (called ReLU) to the resulted frame to introduce non-linearity to the model.

Eventually, there are also fully connected layers at the end of the network. The last set of frames obtained from convolution operations is flattened to get a one-dimensional vector of neurons. From this point we put a standard, fully-connected neural network. At the very end, for classification problems, there is a softmax layer. It transforms results of the model to probabilities of a correct guess of each class

Apply the model and plot the graphs for accuracy and loss

We will compile the model and apply it using fit function. The batch size will be 100. Then we will plot the graphs for accuracy and loss. We got average validation accuracy of 98.6% and average training accuracy of 92.3%.

Accuracy on test set

We got a accuracy of 91.7% on test set.

Saving the Trained Model

- Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or . pkl file using a library like pickle .
- Make sure you have pickle installed in your environment.

- Next, let's import the module and dump the model into . h5 file

V.RESULTS AND DISCUSSION

The improved MobileNet model demonstrated excellent performance in detecting and classifying multiple co-occurring cotton plant diseases along with their severity levels. Compared to the standard MobileNet and other baseline CNN models, the enhanced version achieved higher accuracy, precision, and recall across all disease classes. It effectively handled complex scenarios where multiple diseases appeared simultaneously on a single leaf, accurately identifying each condition and its severity. The lightweight design allowed for fast inference, making it suitable for real-time use on mobile and edge devices. These results highlight the model's potential as a practical tool for precision agriculture and timely disease management.

In this page, disease name and recommendations will be displayed

VI.CONCLUSION

In conclusion, the proposed system effectively utilizes an improved MobileNet model combined with image processing techniques to detect and classify multiple cotton leaf diseases while also assessing their severity levels. By analyzing the geometric features such as area and perimeter of the leaves, the model provides accurate and efficient results that can assist farmers in making informed decisions to protect their crops. The lightweight nature of the MobileNet architecture ensures suitability for deployment on mobile and edge devices, promoting widespread use in agricultural settings.

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