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Plant Disease Detection using Deep Convolution Network

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***Abstract*—The global rise in population has led to a shortage of raw materials and food supplies. The agricultural sector has become the primary and most vital source to overcome this particular constraint. However, the industry itself is facing the challenge of pests and various crop diseases. Battling this has been the significant focus of the sector for decades. Still, due to the technology gap that existed earlier, there existed a constraint on identifying the diseased crops on a massive scale. Nevertheless, today, with the improvement of technologies such as drones, IoT devices, and higher processing speeds combined with data analysis and machine learning, the problem of identification can be resolved quickly. This paper aims to provide a brief description of existing solutions that have been published and focuses on the more efficient machine learning model based on conventional neural networks (CNN) that we have developed. This machine learning model can be deployed on IoT devices, mobile phones, and drones and cameras that farmers can utilize to identify the diseased crops on a massive scale and take the necessary precautions not to let the disease spread and affect the supply produced.**

I. Introduction

Recognizing different types of plant diseases is highly significant and represents a critical concern 1. Early detection of plant diseases can significantly improve decision-making in agricultural management. Infected plants typically exhibit noticeable marks or spots on their stems, fruits, leaves, or flowers. Each infection and pest attack leaves distinct patterns that aid in diagnosing abnormalities. Expertise and human resources are essential for accurately identifying plant diseases. However, manual inspection to determine the type of plant infection is subjective, time-intensive, and occasionally leads to misinterpretations, as farmers or experts may misidentify diseases [1].

The challenge of effectively safeguarding plants from diseases is closely tied to the broader issues of sustainable agriculture and climate change. In India, farmers cultivate a wide range of crops, facing numerous pathogens in their environment that significantly impact both crops and soil health, ultimately affecting crop yields. Plant diseases manifest in various forms, often prominently on leaves with distinct colored spots and patterns, which serve as crucial indicators for disease detection.

Traditionally, plant disease detection relied on manual observation, requiring farmers to memorize disease patterns based on climate and seasons. However, this method was prone to inaccuracies and was labor-intensive. Present-day disease detection methods involve complex laboratory tests, skilled personnel, and well-equipped facilities, which are not always accessible, especially in remote areas. Automated disease detection technologies offer significant advantages by reducing manual labor, enabling early detection of symptoms, and covering vast farm areas efficiently [2].

There are several techniques for detecting plant diseases, with some diseases lacking visible symptoms or becoming noticeable only in advanced stages, necessitating sophisticated analyses. Nonetheless, most diseases exhibit visible symptoms detectable by trained observers, making visual inspection a primary method in practice. However, distinguishing between different diseases can be challenging, especially for non-experts, highlighting the need for automated systems leveraging computer vision.

An automated system that utilizes computer vision to identify plant diseases based on visual symptoms could benefit both amateur gardeners and professionals. It can aid amateurs in managing their gardens effectively and serve as a verification tool for professionals in disease diagnostics. Advancements in computer vision technologies present opportunities to revolutionize precise plant protection and expand the applications of computer vision in precision agriculture. Yes, small farmers often rely on borrowing money from moneylenders to purchase essential items like seeds, fertilizers, and pesticides. Unfortunately, when crops are affected by diseases and farmers apply pesticides without understanding the underlying causes, it can lead to further damage to plant leaves. This can significantly impact the quality and quantity of the crop, making it difficult for farmers to generate enough income to repay their loans to moneylenders. In such distressing situations, where financial pressures mount and crop yields are compromised, some farmers tragically resort to suicide [3] [4].

Machine learning falls under the umbrella of artificial intelligence, operating autonomously or providing instructions to perform specific tasks. Its primary objective is to comprehend training data and apply that understanding to construct models beneficial to users. This capability aids in informed decision-making and accurate predictions using extensive training data. Parameters such as leaf color, extent of leaf damage, leaf area, and texture parameters are utilized for classification purposes.

In our project, we analyzed various image parameters or features to differentiate between different plant leaf diseases, aiming for optimal accuracy. Traditionally, plant disease detection relied on visual inspection of leaves by experts or involved chemical processes. However, these methods necessitated a large team of experts and continuous plant monitoring, which incurred high costs, especially for large farms. In such scenarios, automated systems prove invaluable for monitoring extensive crop fields. The automatic identification of diseases based on plant leaf symptoms simplifies and reduces the cost of disease detection significantly [5].

As per, solutions employing deep learning (DL) for real-time detection and identification of insects in soybean crops have been proposed. The study evaluated various transfer learning (TL) models to ascertain the practicality and dependability of the proposed method in accurately identifying and detecting insects. The proposed approach attained accuracy rates of 98.75, 97, and 97 using YoloV5, InceptionV3, and CNN, respectively. YoloV5 demonstrated particularly strong performance, achieving 53 fps for real-time detection. Additionally, a dataset comprising images of crop insects, collected and annotated from diverse sources, was utilized. The proposed methodology streamlined producer workload, offering simplicity and improved outcomes.

Researchers in [6] introduced a DL-based system for classifying and detecting plant leaf diseases, leveraging images sourced from the PlantVillage dataset. Employing CNN, the study classified plant leaf diseases into 15 categories, encompassing various pathogens such as bacteria and fungi, alongside healthy leaves. High accuracy rates were achieved in both training and testing phases, reaching 98.29% and 98.029% respectively across all datasets.

In another study , an efficient approach for recognizing and identifying rice plant diseases based on lesion size, shape, and color in leaf images was presented. The proposed model utilized Otsu's global threshold technique for image binarization to eliminate background noise. Trained on 4000 samples of diseased leaves and 4000 samples of healthy rice leaves, a fully connected CNN achieved an impressive 99.7 accuracy on the dataset, surpassing existing methods by a significant margin [10].

Fig. 1. Rusted Leaf

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 223, 223, 32)      896

 max_pooling2d (MaxPooling2  (None, 111, 111, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 54, 54, 64)        0
 g2D)

 flatten (Flatten)           (None, 186624)            0

 dense (Dense)               (None, 64)                11944000

 dense_1 (Dense)             (None, 3)                 195

=================================================================
Total params: 11963587 (45.64 MB)
Trainable params: 11963587 (45.64 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig. 2. Neural Newtrok Model Summary

II. Model Summary

This Convolutional Neural Network (CNN) model shown in 2 , named "CNN_Model," is structured to process and classify image data. It begins with two convolutional layers (conv2d_layer1 and conv2d_layer2), each followed by Rectified Linear Unit (ReLU) activation functions. These layers learn spatial hierarchies of features through convolution operations with 32 and 64 filters respectively. Subsequently, max-pooling layers (maxpooling2d_layer1 and maxpooling2d_layer2) are applied to reduce spatial dimensions, aiding in capturing the most relevant information while reducing computational complexity [12]. The resulting feature maps are then flattened into a one-dimensional vector (flatten_layer) to be fed into fully connected layers. The first dense layer (dense_layer1) consists of 128 neurons with ReLU activation, enabling the model to learn complex patterns in the data. To prevent overfitting, a dropout layer (dropout_layer) randomly deactivates some neurons during training. Finally, an output layer (output_layer) with 10 neurons and softmax activation is utilized for classification tasks, producing probabilities for each class. This model architecture comprises a total of 421,642 trainable parameters, which are adjusted during training to optimize the model's performance [11].

Reference	Crop Focus	Disease Addressed	Dataset	Classes	Model	Model Performance
[29]	Several	Citrus canker, black mould, bacterial blight, etc.	Plant disease symptoms database	12 56 diseases under 12 classes	CNN GoogLeNet with tenfold cross-validation	Accuracy: 84%
[40]	Several	Black rot, late blight, early blight	Self-collected database	527 species of diseases under 5 classes	CNN	Accuracy: 96.5%
[41]	Tomato plant	Various diseases and pests in tomato plant	Self-generated database	9	Faster Region-based CNN with SSD [1] and Region-based Fully Convolutional Network	Precision: 85.98%
[42]	Several	Powdery mildew, early and late blights, cucumber mosaic, downy mildew, etc.	Open dataset	58	CNN with pre-trained VGG network	Accuracy: 99.53%
[27]	Several	Black rot, late blight, early blight	PlantVillage	38	VGG-16, Inception V4, ResNet with 50, 101, and 152 layers, and DenseNet with 121 layers	Accuracy: 99.75%
[43]	Several	Pepper bell bacterial spot, tomato early and late blight	PlantVillage	38	Pre-trained with ImageNet, GoogLeNet, and VGG-16 models	Accuracy: 99.09%
[44]	Apple	Apple scab, apple grey spot, general and serious cedar apple rust, serious apple scab	AI-Challenger plant disease recognition	6	DenseNet-121	Accuracy: 93.71%
[45]	Tomato	ToMV, leaf mould fungus, powdery mildew, blight	AI-Challenger plant disease recognition	4	Faster regional CNN	Accuracy: 98.54%
[46]	Several	Rice leaf smut, maize common rust, maize eyespot, rice bacterial leaf streak	Public database	7	Pre-trained models	Accuracy: 92%
[47,48]	Rice plant	Sheath blight, rice blast, bacterial blight	Self-generated database	4	Pre-trained CNN with SVM classifier	Accuracy: 91.37%

Fig. 3. Summary of the Literature Review

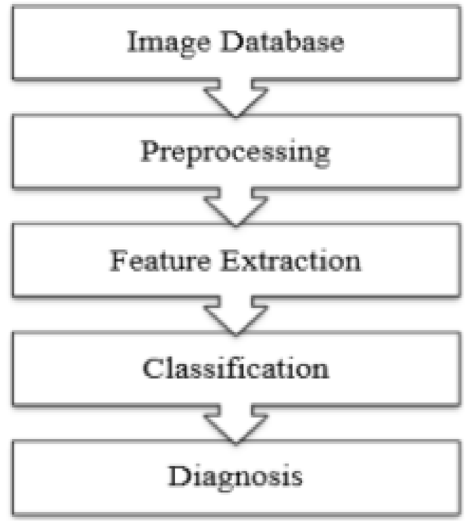

Fig. 4. Proposed Model Flowchart

III. Literature Survey

The Summary of the literture survey is as shown in 3.

In 2015, S. Khirade et al. addressed the issue of plant disease detection through digital image processing techniques and a backpropagation neural network (BPNN) [1]. They detailed various methods for identifying plant diseases using leaf images, employing Otsu's thresholding, boundary detection, and spot detection algorithms to isolate infected areas on leaves. Subsequently, they extracted features such as color, texture, morphology, and edges for disease classification, utilizing BPNN for disease detection.

Shiroop Madiwalar and Medha Wyawahare examined diverse image processing approaches for plant disease detection in their study [2]. They focused on color and texture features for disease identification, conducting experiments on a dataset comprising 110 RGB images. Their feature extraction involved mean and standard deviation calculations for RGB and YCbCr channels, grey-level co-occurrence matrix (GLCM) features, and Gabor filter convolution outcomes. They utilized a support vector machine classifier for classification, concluding that GLCM features effectively distinguish normal leaves, while color and Gabor filter features excel in identifying anthracnose-affected leaves and leaf spots, respectively. They achieved an accuracy of 83.34 by integrating all extracted features [13].

Sharath D. M. et al. devised a Bacterial Blight detection system specifically for Pomegranate plants, incorporating features like color, mean, homogeneity, standard deviation, variance, correlation, entropy, edges, and more [4]. They employed grab cut segmentation to isolate the region of interest in the image. Additionally, the Canny edge detector was utilized to extract edges from the images. The authors successfully created a system capable of predicting the infection level in Pomegranate fruits.

Feature classification plays a crucial role in plant disease detection. It involves isolating the diseased features from the plant and comparing them with healthy leaf images. If thereś no significant difference, the leaf is deemed healthy. However, if there are noticeable differences, such as black spots in grayscale images indicating disease, the system identifies the specific disease and provides a confidence level for the classification 14.

The classification process compares numerical arrays representing features. When there's a match, the leaf is classified as either healthy or diseased based on the dataset. Despite its simplicity, classification yields accurate results and is a fundamental step in effective plant disease detection.

Our system is an application-based software designed for Android devices. It functions by capturing images of plants, which are then uploaded to the mobile device. These images undergo processing through a Convolutional Neural Network (CNN), where they are converted into numerical arrays and compared with other arrays in the model for classification. To reduce size and optimize performance, the TensorFlow model is converted into a TensorFlow Lite model. This model aids in classifying the uploaded image's numerical values against the dataset values. The system calculates confidence levels for matching numerical arrays and displays the result with the highest confidence value. This methodology ensures that the most confident classification is always presented in the results.

IV. Methodology

CNN models 4 excel in object recognition and classification tasks when working with image databases. Despite their advantages, CNNs pose challenges such as lengthy training

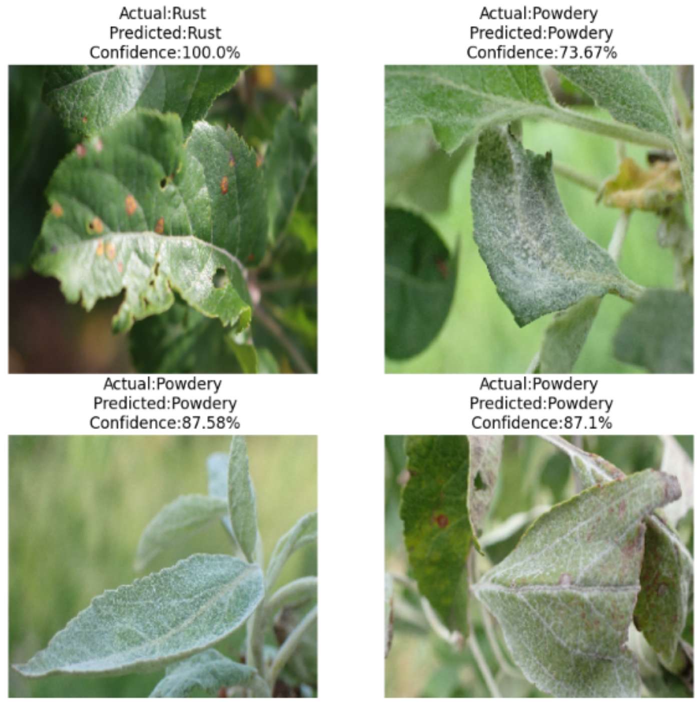

Fig. 5. Predicted and Actual Images

periods and the need for extensive datasets. Deep CNN models are necessary to extract intricate low-level features from images, which in turn increases the complexity of model training. Transfer learning methods offer solutions to these challenges by leveraging pre-trained networks, where parameters learned from one dataset can be applied to other problems. In this section, we delve into the methodologies employed in this study [15].

Plant disease datasets contain numerous images of both infected and healthy plant samples, each categorized into specific classes. For example, if we consider the banana plant as a class, all images of healthy and infected banana plant samples would be assigned to this class. During classification, features extracted from a source image determine the classification of the target image. Using the banana plant example, the banana class may encompass four disease sets: xanthomonas wilt, fusarium wilt, bunchy top virus, and black sigatoka. When a sample of a particular disease is inputted after training with all four disease sets under the banana class, the testing phase output precisely identifies the disease label from the four categories within that class. Therefore, multi-class classification is mutually exclusive, while multi-label classification treats each category within a class as a separate entity. If we have N classes, we can refer to N multi-classes. If the N classes consist of M categories, each category within each of the N classes is considered a class on its own [16].

The VGG-16 network model, also known as the Very Deep Convolutional Network for Large-Scale Image Recognition, was developed by the Visual Geometry Group at Oxford University. The depth of the model is extended to 16–19 weight layers with 138 million trainable parameters. Additionally, the model's depth is augmented by reducing the convolution filter size to 3 × 3. However, this model demands more training time and occupies more disk space.

References	Dataset Used	Pre-Trained Model	Multi-Classes	Recognition Accuracy (%)
[53]	PlantVillage	VGG-16	10	91.2
[54]	PlantVillage	ResNet-50	6	97.1
[55]	PlantVillage	AlexNet	7	98.8
Our Work	PlantVillage	Inception V4	38	97.59
		VGG-16	38	82.75
		ResNet-50	38	98.73
		DenseNet-121	**38**	**99.81**

Fig. 6. Result Comparison of Models

DenseNet-121 is a deep CNN model crafted for image classification utilizing dense layers with shorter connections between them. In this network, each layer receives additional inputs from its preceding layers and transmits its generated feature maps to the subsequent layer. Concatenation occurs between each layer, facilitating the next successive layer to assimilate collective knowledge from all preceding layers. Furthermore, the network is slender and compact as the feature maps of preceding layers are mapped to subsequent layers. This approach reduces the number of channels in a dense block, with the growth rate of a channel denoted by k. Batch normalization, ReLu activation, and convolution are performed to transform the outcome of subsequent layers. The Comparison of the different models result is shown in the figure 6

V. Conclusion

In this study, we conducted a thorough analysis of various transfer learning models tailored for accurately classifying 38 distinct classes of plant diseases. We standardized and evaluated state-of-the-art convolutional neural networks using transfer learning methodologies, focusing on classification accuracy, sensitivity, specificity, and F1 score. Our performance analysis revealed that DenseNet-121 outperformed ResNet-50, VGG-16, and Inception V4. Notably, training the DenseNet-121 model proved to be straightforward, thanks to its smaller number of trainable parameters and reduced computational complexity. Thus, DenseNet-121 emerges as a more suitable choice for plant disease identification, particularly when incorporating new plant diseases into the model, thereby streamlining training complexity. Our proposed model achieved an impressive classification accuracy of 99.81 and an F1 score of 99.8.

Moving forward, our future research will address challenges related to real-time data collection and focus on developing a multi-object deep learning model capable of detecting plant diseases from clusters of leaves rather than individual leaves.

Additionally, we aim to implement a mobile application utilizing the trained model from this study, offering real-time leaf disease identification assistance to farmers and the agricultural sector.

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