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Image based Chili Crop Disease Prediction Using Deep Transfer Learning

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Abstract— Crop diseases have a terrible impact on food protection and can result in considerable reductions in both the supply and quality of agricultural products. Human professional have traditionally been relying on to diagnose crop diseases caused by insects, pests, virus, bacteria, fungal, inadequate nutrition, or adverse environmental conditions. This, however, is costly, time demanding, and in some situations unworkable. Thus, in the area of agricultural information, the automatic identification of crop diseases is significantly required. Many strategies have been presented to solve this challenge, with deep learning becoming as the preferred approach due to its outstanding performance.This research describes a method for detecting chili leaf diseases using a deep convolutional neural network. We compared performances of four architectures: MobileNet, Inception-ResnetV2, EfficientNetB0, and DenseNet. The proposed approach evaluated the findings using measures such as accuracy, loss and time. Our model compares favorably to EfficientNetB0 with an accuracy of 0.995, a loss of 0.023, and time is 5 minutes 45 seconds. EfficientNetB0, a compact deep learning architecture has fine tuned to classify two forms of chili leaf diseases. The method was tested on 2475 photos from the Plant Village dataset.

Keywords- Plant diseases; Convolultional Neural Networks; Deep Learning, Transfer Learning; MobileNet; Inception-ResnetV2; EfficientNetB0; DenseNet.

I. INTRODUCTION

India is a commercial producer of chili. The largest producer, consumer, and exporter of chili in the world is India. In India, the value of chili export in 2018-19 is Rs. 5930.12 Crores and it is doubled its value i.e. Rs. 10773.59 Crores in 2022-23 [1]. Chili crop is easily damaged by its diseases. If these diseases are recognized early and corrective actions are implemented, crop yield and quality may be preserved. Early signs of the chili disease appear on several plant parts, but leaves in particular show symptoms such color changes that may be seen, spots, and blight. The state-of-the-art among many computer vision methods for recognizing images has been built up of machine learning and deep learning algorithms. The human selection of features is necessary when using the traditional computer vision approach for plant disease diagnosis [2]. Deep Learning (DL) techniques [3] which include thousands or even millions of tunable parameters now produce the best results for image classification.

Rangarajan et al. [4] utilizes the tomato crop leaf images from the PV dataset to distinguish six diseases from healthy leaves. The results shown that higher accuracy 97.29%, of and 97.49% respectively, using 2 separate DL models, VGG16 and AlexNet along with transfer learning and hyper parameter tuning. The impact of modifying the learning rate, size of the mini batch and number of images results variation on classification accuracy and execution time has also been demonstrated.

A real-time autonomous plant disease detection system applying different deep Learning architectures was proposed by Rishikeshwar et al. [5]. After performing hyper parameter optimization, the model generates accuracy levels of up to 95% with 400 real leaf images and up to 98% with 3600 enhanced datasets. The models are trained using actual crop leaf images that were taken in a real agricultural field. The projected the result from the model is captured, processed, and displayed via a simple IoT web application.

In 2020, Siti Zulaikha Muhammad Zaki et al. [6] proposed a system that uses MobileNet V2 and a Compact deep learning architecture to detect three different tomato diseases. On 4,671 images from the PV dataset, the algorithm is tested. The findings demonstrate that MobileNetV2 can accurately detect the disease with up to 95.6% accuracy.

Oyewola, et al [7] demonstrated that deep learning with residual connections exceeds ordinary convolution neural networks (DRCNN) in identifying various diseases in cassava plants from Cassava Dataset with an accuracy of 96.7%. Used distinct block processing to retain information contains in the images.

Deep Convolutional Neuro-Fuzzy Method (DCNFM), which combines one of the most sophisticated machine learning variants, namely deep CNNs, and the uncertainty handler known as fuzzy logic, was proposed by Kumar VV et al. [8] as a system to detect real-time images of rice diseases. When working with unstructured data, the synthesis combines the advantages of fuzzy logic with DCNNs to extract important features from uncertain and ambiguous datasets. When compared to the traditional CNN model, the DCNFM's detection/recognition rate of 98.17% is determined to be much more successful.

Using a pre-trained DenseNet model and reweighted cross-entropy loss, Rabbia M. et al. [9] proposed a plant disease detection system. This system is more reliable at detecting potato leaf diseases. On the testing set, the algorithm's performance was evaluated and the accuracy result was 97.2%. Table 1 represents the previous works [10] to detect plant diseases using deep learning.

TABLE I. PREVIOUS WORKS WHICH USED DEEP LEARNING

Reference no	Year	Crop	Number of Classes	Number of images	Algorithm	Accuracy
7	2021	Cassava	5	5656	DRCNN	96.75
8	2022	Paddy	4	_	DCNFM	98.17
9	2023	tato	5	3852	DenseNet	97.2
11	2019	Grape	4	200	Deep Siamese convolutional network	90
12	2020	Rice	5	1426	Small CNN	93.3
13	2019	Potato	2	2465	Faster R-CNN	90
14	2019	Wheat	4	8178	ResNet50	96
15	2020	Not Mentioned	19	20,000	CNN	98
16	2019	Not Mentioned	79	46135	GoogLeNet	80
17	2020	Multiple	38	54,305	VGG16	97.8
18	2019	Multiple	38	54,306	NASNet	93.5
19	2020	Not Mentioned	38	60000	InceptionV3	96

The parameters of MobileNet, Inception-Resnet V2, EfficientNet B0, and DenseNet are trained in proposed study to classify chili leaf diseases into their corresponding classes and analyzed the results based on hyper parameters includes Dropout, optimizer selection, batch size learning rate and time. Pepper, a subset of the Plant Village dataset includes Pepper Bacterial leaf spot and healthy classes—which includes 1478 healthy and 997 images of the disease Plant Village (PV) Dataset [20]. The training and testing subsets of the dataset are divided in the following proportions: 80:20, 75:25, and 70:30.

II. MATERIALS AND METHODS

This section discusses the details about dataset and methods

A. Dataset Acquisition

The proposed system used Plant Village Dataset to detect the chili diseases. 2475 images were extracted from the PV dataset that includes 1478 images of Pepper healthy and 997 images of Bacterial leaf spot.

B. Methods

a. Deep learning

DL [3] is a state-of-the-art machine learning (ML) technology that employs a complex network of artificial nodes with numerous hidden layers. Many methods used prior to the introduction of DL classify tasks using semantic features information. Semantic features include corners, edges, shapes, etc. A DL approach does not need features to be designed in advance. These features are the outcome of optimal automated learning. Since these features are not handcrafted, this technique is capable of handling a variety of data modes [4].

b. Transfer Learning

Transfer Learning [21] is a ML technique in which a model that has been trained on a specific task is repurposed and fine-tuned for a related but distinct activity. The goal of transfer learning is to use the knowledge gained from a previously trained model to tackle a new but similar problem. This is beneficial when there isn't enough data to train a new model from scratch, or when the new task is similar enough to the original that the pre-trained model can be customized for the new challenge with only minor changes.

1. MobileNet

A deep learning architecture called MobileNet is targeted towards mobile platforms, which have constrained computational resources. Google later releases an updated version, known as MobileNet [22], with just minor changes made to the first version. The network's foundation, which is separable convolution, remains unchanged. Images from ImageNet were used to train version 2 of MobileNet. According to the paper [24], although with improved precision,

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the number of parameters used was lowered from 4.24 million to just 3.47 million. The images are 224x224 in size.

2.Inception-ResNetV2

The Inception-ResNetV2 [23] CNN was trained on over a million images from the ImageNet collection. It is created by combining the Residual connection and Inception structure. Multiple sized convolutional filters are mixed with residual connections in the Inception-ResNet block. The introduction of residual connections not only solves the degradation issue caused by deep structures, but it also shortens the training period. The image input size for the network is 299x 299.

3.EfficientNetV2

EfficientNetV2 [24] is a kind of CNN that has higher parameter efficiency and training speed than previous models. When creating these models, the authors used a combination of training-aware neural structure and scaling to simultaneously optimize training speed. The models were found utilizing a search space that has been expanded with new techniques like Fused-MBConv. Smaller expansion ratios for MBConv are preferred by EfficientNetV2 because they have less memory access overhead. EfficientNetV2 supports smaller 3x3 kernel sizes, however it also employs more layers to compensate for the narrower receptive field caused by smaller kernel sizes. The last stride-1 step from the original EfficientNet is removed in EfficientNetV2, perhaps due to its large parameter number and memory access expense.

4.DenseNet

A DenseNet [25] is a type of CNN that utilizes dense connections across layers via Dense Blocks, which directly connect all levels. To retain the feed-forward character, each layer acquires extra inputs from every layer prior and sends them on to all subsequent ones. Each layer receives collective information from the layers above it. Because each layer obtains feature maps from the layers above it, the network can be thinner and more compact, resulting in fewer channels. As a result, it is more efficient in terms of computation and memory. DenseNet was designed primarily to improve precision because of the vanishing gradient in high level neural networks as a result of the large distance between input and output layers, leading to information that vanishes prior to achieving its goal. The image input size for the network is 224x224.

III. RESULTS AND DISCUSSIONS

In this paper, the experimental results are analyzed using HP Omen Intel core i7-10750H@ 1.6GHz CPU with 8 GB RAM, 1TB SSD and NVIDIA GTX 1650ti 4GB. Plant Village dataset is used to detect the chili leaf diseases. The experimental results are tested on the images were divided into training and testing and their proportions includes 80:20, 75:25 and 70:30. Hyper-parameter configurations of the pre trained networks MobileNet, Inception-ResnetV2, EfficientNetB0, and DenseNet are tested that includes number of images, Dropout, optimizer selection, batch size and learning rate. The testing procedure is carried out sequentially, with the best configuration of each hyper-parameter tested independently to determine the optimal value. Experimental results shown that the 75:25 train and test split tested on EfficientNetB0 gives 0.995 accuracy with RMSprop optimizer, learning rate 0.001, dropout 0.2 and taken less time i.e. 5 minutes 45 seconds are tabulated in Table 2.

TABLE II. EXPERIMENTAL RESULTS

Model	Distribution	Optimizer	Epoch	Time	Accuracy	Loss
MobileNet	80-20	SGD	50	4m 14sec	0.981	0.078
		RMSprop	50	4m 8sec	0.988	0.02
		Adam	50	4m 13sec	0.988	0.033
	75-25	SGD	45	3m 46sec	0.964	0.113
		RMSprop	45	3m 44sec	0.984	0.042
		Adam	45	3m 32sec	0.984	0.041
	70-30	SGD	30	2m 28sec	0.961	0.117
		RMSprop	30	2m 26sec	0.98	0.03
		Adam	30	2m 24sec	0.988	0.028
Inception-ResnetV2	80-20	SGD	50	17m 5sec	0.925	0.202
		RMSprop	50	16m 54sec	0.969	0.06
		Adam	50	16m 56sec	0.969	0.054
	75-25	SGD	45	14m 59sec	0.948	0.158
		RMSprop	45	14m 55sec	0.99	0.05
		Adam	45	14m 54sec	0.995	0.034
	70-30	SGD	30	10m	0.938	0.217
		RMSprop	30	9m 53sec	0.98	0.071
		Adam	30	9m 50sec	0.984	0.04
Efficient NetB0	80-20	SGD	50	6m 39sec	0.962	0.17
		RMSprop	50	6m 49sec	0.98	0.014
		Adam	50	6m 55sec	0.98	11
	75-25	SGD	45	5m 51sec	0.943	0.184
		RMSprop	45	5m 45sec	0.995	0.023
		Adam	45	5m 53sec	0.99	0.01
	70-30	SGD	30	3m 59sec	0.953	0.2
		RMSprop	30	3m 57sec	0.984	0.034

		Adam	30	3m 58sec	0.992	0.017
DenseNet	80-20	SGD	50	9m 8sec	0.956	0.116
		RMSprop	50	9m 15sec	0.99	0.014
		Adam	50	9m 13sec	0.99	0.022
	75-25	SGD	45	8m 7sec	0.969	0.121
		RMSprop	45	8m 3sec	0.99	0.038
		Adam	45	7m 56sec	0.99	0.014
	70-30	SGD	30	5m 19sec	0.973	0.125
		RMSprop	30	5m 19sec	0.992	0.039
		Adam	30	5m 20sec	0.99	0.018

Figure 1 represents Accuracies of Models obtained on 3 Optimizers i.e. SGD, RMSProp, Adam with learning rate 0.001, dropout 0.2 and split ratio of train and test images is 75:25. It is observed from the figure1 SGD optimizer gives less compared to the others. Figure 2 represents the 4 models and their time to complete model build per epoch in terms of seconds. Inception-ResNetV2 model built taken more time among all i.e. 20 seconds.

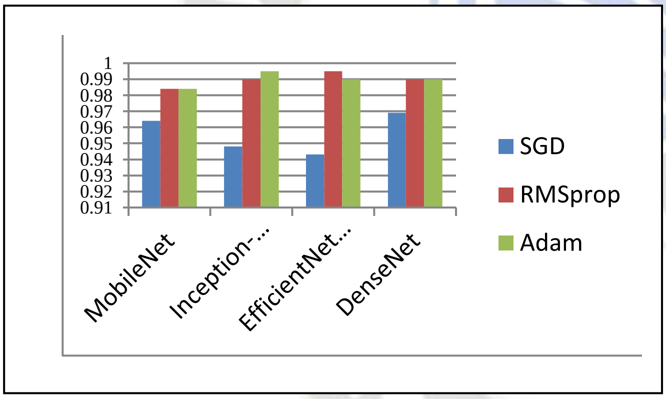

Figure 1. Accuracies of Models on 3 Optimizers.

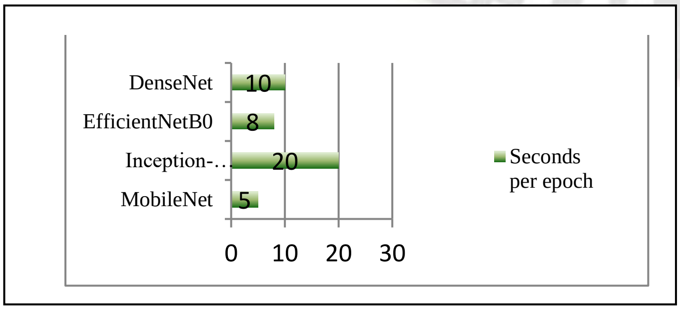

Figure 2. Models and their time to complete model build per epoch

TABLE III. COMPARISON OF PAST SIMILAR WORKS WITH PROPOSED WORK

Reference no	Year	Crop	Number of Classes	Number of images	Algorithm	Accuracy	Does proposed method integration into small computing devices efficient?
4	2018	Tomato	6	13262	VGG16 and AlexNet	97.49	No
5	2019	—	—	3600	CNN	98	Yes
6	2020	Tomato	3	4671	MobileNet V2	95.6	Yes
7	2021	Cassava	5	5656	DRCNN	96.75	No
8	2022	Paddy	4	–	DCNFM	98.17	No
9	2023	Potato	5	3852	DenseNet	97.2	Yes
Proposed work	2023	Chili	2	2475	EfficientNetB0	99.5	Yes

Although the past and proposed experiments were examined under various system requirements such as number of images, number of classes, GPUs and time taken to build the model, the comparison is represented in Table 3. According to the Table 3 [4,7,8] were build under deep layers as these models requires more resources and time. [5,6,9 and proposed work] needs less resources as these models are compact and efficiently integrated into small computing devices.

IV. CONCLUSION

Deep learning approaches, notably CNNs, have demonstrated promising performance in handling the majority of the difficult plant disease classification challenges. Using fine-tuned Deep transfer learning, the suggested approach in this research can categorize the chili leaf images from the Plant Village dataset. The comparison findings showed that EfficientNetB0 achieved 0.995accuracy in 5 minutes 45 seconds using RMSProp optimizer and Inception-ResNetV2 achieved 0.995 accuracy in 14 minutes 54 seconds using Adam optimizer. The EfficientNetB0 and MobileNet models classified chili diseases in a fraction of the time. Even if the yield is large, these models can be integrated with smart computer devices or UAVs. In the future, the classification dataset can be acquired from a variety of sources, including geographical areas, cultivation methods and more number of images with other crops.

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