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Plant Disease Identification Using Convolutional Neural Network and Transfer Learning

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Abstract: Agriculture is an important part of our economy and has attracted our attention since the Middle Ages. India's population is mainly dependent on agriculture, accounting for 60~70%. Global crop losses from a variety of reasons, including weeds, disease, and arthropods, have increased at an alarming rate, from about 34.9% in 1965 to about 42.1% in the late 1990s. Bacteria and fungi can cause many diseases in plants. Many diseases such as Early blight and late blight are fungi that afflict plants. In our research, we provide CNN models and algorithms for detecting leaf diseases in crops. This study discusses the feasibility of CNNs and Transfer Learning for classifying plant diseases. This model is built using a basic CNN architecture to classify potato diseases. From the Plant Village database, 2,152 samples containing photos of leaves in three classes with images of healthy leaves were obtained and used for initial training to check the feasibility of plain CNN and then dataset with 54306 plant images was used to train the bigger plain CNN and Resnet152v2 and Inceptionv3 Architecture for detecting plant diseases using Transfer Learning. The photos were taken in an unstructured environment. The constructed model obtained a classification accuracy of 97.57%, clearly demonstrating the feasibility of utilizing CNNs to classify plant diseases.
Keywords: Deep Learning, CNN, Transfer Learning plant disease

I. INTRODUCTION

Agriculture now serves quite a lot of purposes as well as providing food for the expanding population. But plant diseases are jeopardizing the survival of this important source. Plant diseases significantly reduce the productivity of agriculture and forestry, resulting in economic losses. Early Blight and Late Blight are two common potato diseases [30]. They can have a negative impact on farmland and potato plants. It is possible to notice late blight and early blight on the leaves of the plant, but it takes a lot of time to do it manually. Early detection and identification of plant diseases is important for rapid response. Plant diseases alone cause 20–40% of crop yield losses, which has a significant impact on the agriculture sector. There are numerous methods for identifying plant disorders. Some diseases don't have any obvious symptoms, or they don't show up until it's too late to do anything about it. In these circumstances, complex analysis is required, frequently using potent microscopes. Only portions of the electromagnetic spectrum that are invisible to humans can sometimes be used to detect the indications [2]. But most diseases cause some kind of outward expression. Signs of disease may appear on leaves, stems, fruits, seeds, or other parts of the plant. This study focuses on identifying and classifying plant diseases using symptoms that appear on plant leaves. In most cases, humans make a visual diagnosis or at least a preliminary assessment of the disease [2]. The disease may be easily recognized by a qualified specialist. Unfortunately, there are rarely local experts who can provide farmers with data-driven analysis and advice. Therefore, it is important to look for a quick, automatic, affordable and accurate way to identify plant diseases. Agricultural research uses machine learning techniques such as artificial neural networks (ANNs), decision trees, K-means, k-nearest neighbors, and support vector machines (SVMs) [12]. Traditional methods for classifying images rely on manually created features such as SIFT [22], HoG [23], and SURF [24], and then apply learning algorithms to these feature spaces. They found that the effectiveness of each of these techniques largely depended on the underlying preset characteristics [14]. However, the effectiveness and efficiency of the learned representation is shown by recent machine learning trends. The fundamental advantage of representation learning is that it can automatically analyze large collections of photos to find features that allow images to be classified with minimal error [15]. Convolutional neural networks (CNNs) are one of the most widely used techniques used to classify images and recognize objects [14, 15, 16, 17]. Convolutional neural networks (CNNs), a subset of deep neural networks (DNNs) used for image processing, are models of the human visual system. It was proposed to adopt a different CNN architecture for object recognition. Both LeNet [5] and AlexNet [6] are used as benchmarks for various activities [7], We tested two well-known baseline image recognition algorithms: Inception, ResNet. There are a total of 15 baseline implementations, including many iterations of these well-known baselines[31].

The development of deep CNN-based architectures is further accelerated by transfer learning techniques. CNN models are first trained on large datasets using transfer learning techniques. A pretrained model is what is used to describe a trained model. In addition, pre-trained models can identify related image patterns from datasets that belong to the same or different domains.
The transfer learning technique frequently prevents overfitting DL structures on short datasets. In addition, the number of DL architecture training iterations required for other datasets is reduced.

The paper's overall contribution can be summed up as follows:

1) We look into a CNN classifier that can distinguish between various plants and the associated plant illnesses. To the best of our knowledge, this is the first study project that has combined the diagnosis of several different plants.
2) For our experiment, we blend six different plants, including Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, pepper, potato, Raspberry, soyabean, squash, strawbeery and Tomato. There were a total of 38 illnesses affecting the 14 plants in the experimental dataset.

The study investigated CNN's ability to identify plant diseases from leaf photographs taken in an uncontrolled environment. The Plant Village [20] database is used to retrieve the training dataset. CNN training data is augmented by data augmentation because it requires a large amount of data.
The paper is organized as follows; part II deals with the previous works conducted in the similar area. Part III describes the steps and the materials used to perform the experiment.In Section IV , the overall architecture of deep CNN is described. The results obtain is presented in part V and it concludes by recommending methods for future improvement. Finally, Section VI concludes the chapter.

II. LITERATURE REVIEW

This section describes the latest developments in the use of CNNs and deep learning architectures in agricultural applications. Before deep learning was developed, various plant diseases were classified using image processing and machine learning techniques [2, 5, 8, 9]. Typically, most of these systems proceed in the manner described below.
Use a digital camera to take your first digital photo. Then, image processing techniques such as image enhancement, segmentation, color space conversion, and filtering are used to prepare the next phase of the photo. The important features are then retrieved from the image and sent to the classifier [10].
Therefore, the type of image processing and feature extraction techniques used determines the overall classification accuracy. However, recent studies have demonstrated that networks trained on general-purpose data can achieve state-of-the-art performance.
CNNs are supervised multi-layer networks that can automatically learn features from datasets. In recent years, CNNs have excelled at nearly all-important classification tasks, displaying state-of-the-art performance. Under the same architecture, it can carry out both feature extraction and categorization [14]. A CNN is a particular type of neural network that has been extensively used to solve several pattern recognition issues, including computer vision, speech recognition, and other related ones. LeCun et al. [21] provided the first inspiration for the CNN, which numerous researchers have since continued to use. The CNN is based on the human visual system. Local receptive fields, shared weights, and spatial or temporal sub-sampling are three architectural principles that CNNs employ to provide some level of shift, scale, and distortion invariance [4].
To classify plant diseases, Sharada P. Mohanty et al. [17] adopted the already built deep CNN architectures AlexNet [6] and GoogLeNet [19]. CNN was taught to recognize 14 crop species and 26 diseases using a public dataset of 54,306 photographs of sick and healthy plant leaves taken in a controlled environment (or no environment). The model was 99.35% accurate. However, when evaluated with a series of photos taken in a different environment than the one used for training, the accuracy of the model dropped to 31.4%. Overall, the results indicate that deep CNNs can be used to classify plant diseases. The results demonstrate that robust computing infrastructure makes CNN a suitable candidate for disease recognition.
However, large labeled collections of datasets are one of the drawbacks and challenges. CNNs are much more accurate because they don't have a huge dataset, but transfer learning techniques have been applied to classify plant diseases. Transfer learning only needs to infer the parameters of the latest classification level to determine the outcome of the classification [32].
The goal of this effort is to build a reliable multi-label transfer learning system that accurately and efficiently identifies plants and their diseases. This chapter describes how to detect and diagnose multilabel plant diseases using deep CNN transfer learning. Transfer learning utilizes information from the original model to enhance the learning of the target task. For better results, reduce the number of training iterations and the amount of data required for transfer learning. In addition, knowledge is often transformed, so the learning procedure improves generalization.

III. MATERIALS AND METHODS

To classify potato plant diseases a large collection of the plant's leaf images is required. The images are down- loaded from the Plant Village database . In this section the methodology followed is discussed in detail.

A. Dataset

Proper and large dataset is required for all classification research during the training and the testing phase. The dataset for the experiment is downloaded from the Plant Village database which contains different plant leaf images and their labels. It contains a collection of images taken at different environment. A dataset containing 2,152 leaf images of three classes including healthy leaves is downloaded for initial traning for plain cnn . We then examine 54,306 pictures of plant leaves with a total of 38 different class designations. We attempt to forecast the crop-disease pair for each class label based solely on the image of the plant leaf. A sample from each crop-disease relationship in the PlantVillage dataset is shown in Figure 1. In all of the methods outlined in this research, we downscale the images to 256 256 pixels before performing the model optimization and making predictions on them.

Since the images were taken in the uncontrolled environment the different lighting condition and background in the training images may bias the neural network. To test this, the experiment was also performed using the grayscale and the segmented version of the database. Sample images of the gray and segmented leaf images are shown in Fig.2 and Fig.3 respectively.

Fig1. Fig2. Fig3.

Fig. 1. sample images from the database A) early blight image, [b-c] leaf images from healthy plant B) healthy leaf image C) healthy leaf image D) late blight

Fig. 2. sample images from the database A) early blight image, [b-c] leaf images from healthy plant B) healthy leaf image C) healthy leaf image D) late blight

Fig. 3. sample images from the database A) early blight image, [b-c] leaf images from healthy plant B) healthy leaf image C) healthy leaf image D) late blight

B. The proposed CNN Model

Different CNN designs are used depending on the situation at hand. Three convolutional layers, each followed by a maxpooling layer, make up the suggested model. The final layer is a dense layer that is completely connected. Each convolutional layer and fully connected layer output is subjected to the ReLu activation function. 32 3x3 kernels from the first convolutional layer are used to filter the input image. Following the application of maxpooling, the result is used as an input for the second convolutional layer, which has 64 3x3 kernels. A flat layer with 256 neurons and 64 completely linked neurons makes up the final convolutional layer before it is followed by a dense layer

TABLE II
ARCHITECTURE OF THE PROPOSED MODEL

Layer	Type	Filter Size	Kernel size
L1	Conv	32	3x3
	Max Pool	-	2x2

L2	Conv	64	3x3
	Max Pool	-	2x2
L3	Conv	64	3x3
	Max Pool	-	2x2
L4	Conv	64	3x3
	Max Pool	-	2x2
L5	Conv	64	3x3
	Max Pool	-	2x2
L6	Conv	64	3x3
	Max Pool	-	2x2
L7	Flatten	256 Neurons	-
L8	Dense	64 Neurons	-
L9	Dense	3 Neurons	-

The model is trained using adaptive moment estimation (Adam) with batch size of 32 for 100 epochs.

Evaluation metrics are first defined in this section. We conclude by presenting an assessment and a thorough analysis.
Metrics, Based on the confusion matrix, we adopted evaluation criteria for precision, precision, and recall. Machine learning and deep learning classification problems predicted by four scales: true positive (TP), true negative (TN), false positive (FP), and false negative are summarized in a confusion matrix (FN). Use these metrics to evaluate the performance of your architecture.
Accuracy: Accuracy defines how many of the correct positive classes predicted by the model are actually positive. Divide the total number of positive examples classified as positive by the total number of predicted examples to get the accuracy value.
Precision: Precision defines all the positive classes the model predicted correctly; how many are actually positive. To obtain the value of precision, the total number of correctly classified positive examples are divided by the total number of predicted positive examples. The equation can be stated as,
9

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

Recall: It defines how much the model predicted correctly among all positive classes. A recall is the ratio of the total number of correctly classified positive examples
divided by the total number of positive examples. The equation can be stated as,

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

F1-score: F1-score gives an overall estimation of the precision and recall of a test subject. It is the harmonic mean of the precision and recall of a test subject. Formally, F1-score can be defined as,

$$F1\_score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

IV. EXPERIMENTAL RESULTS

The dataset is divided into three sections: training (80%), testing (10%), and validation (10%). Tests are conducted on many models with different topologies and learning rates. Trial and error was done to select network parameters such as kernel size, filter size, learning parameters, and activation functions. The results obtained are shown in Table III below.

As you can see from the results, color images have higher classification accuracy than grayscale and segmented images. This shows the importance of color features in the extraction of important features for classification. Three convolutional layers, each followed by a maximum pooling layer, make up a model that provides a high level of classification accuracy.

Table III
Classification Result From Different Models

IMAGES	TEST_ACCURACY	VALIDATION_ACCURACY
Grayscale	95.26	92.19
Color	99.14	98.96
Segmented	99.14	98.48

ReLu activation function is used for each layer. We usedthis model as a base model for further improvements.

The graphs of the training accuracy versus validationaccuracy of the model, is shown in Fig 4

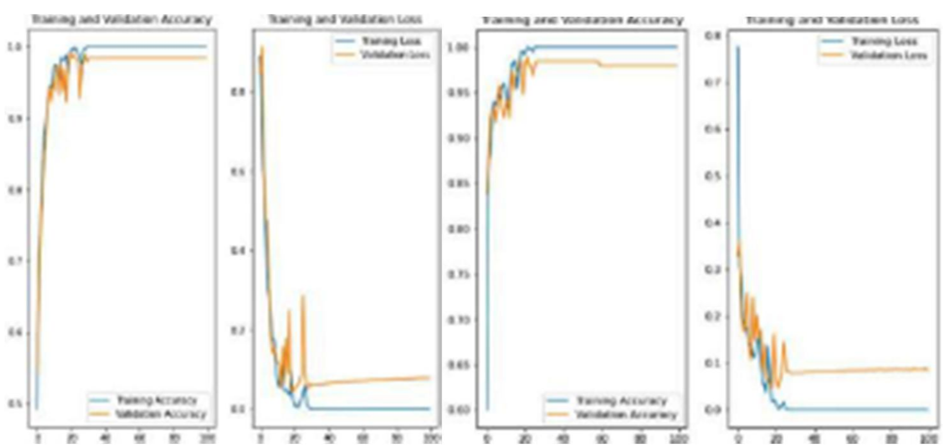

Fig. Training vs Testing Accuracy(color) Fig. Training vs Testing Accuracy(Segmented)

It can be seen from the graphs that the model is overfitting. Overfitting happens when the model fits too well to the training set. It then becomes difficult for the model to generalize to new examples that were not in the training set. Several techniques have been developed to overcome overfitting, such as data augmentation, introducing weight penalties of various kinds such as L1 and L2 regularization and dropout [27].

Experiments were conducted to see the effect of each technique on the performance of the model. Since the dataset is too small when compared to the total number of trainable parameters of the model, the first experiment we did is to increase the training data by rotating, flipping, rescaling of the images. The result obtained when using data augmentation is shown in Fig. 5

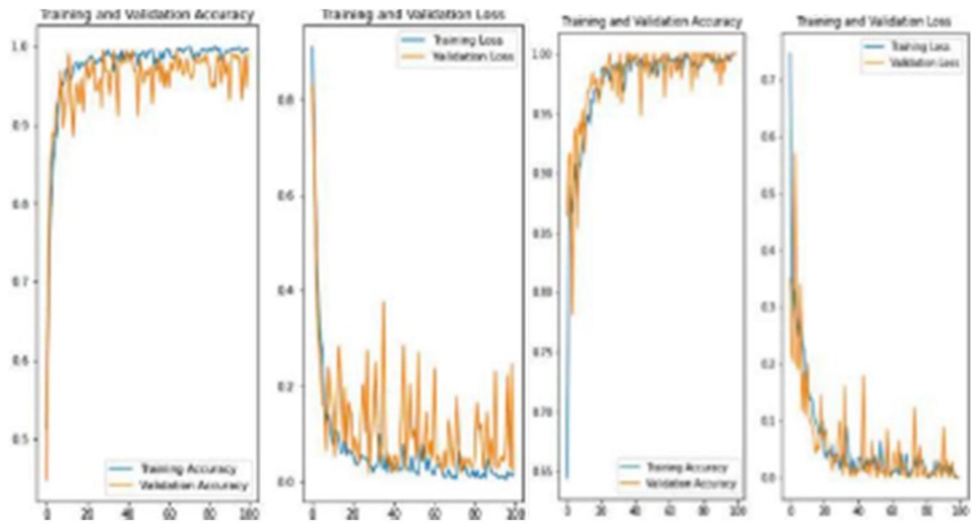

Fig. Training vs Testing Accuracy(color) Fig. Training vs Testing Accuracy(Segmented)

The result shows that data augmentation alone solves over-fitting significantly. It also increases the validation accuracy to 98.87%. This explains the original dataset was so small compared to the total number of trainable parameters of the model and the result is summarized in Table IV below. Both models showed a slight improvement over the performance of the model.

TABLE IV
EFFECT OF DATA AUGMENTATION

IMAGE	TEST_ACCURACY	VALIDATION ACCURACY
COLOR	99.57	98.87
SEGMENTED	99.57	98.96

For The other Plain CNN and the Transfer learning Resnet152v2 and Inceptionv3 Architecture:
For proper evaluation, each model was pre-trained on the ImageNet dataset aside from plain CNN which has now two more conv layers based on previous experiments. Each of the results presented in this paper is presented as a mean of four runs. Each model is trained with a limit of 10 epochs. However, the training is halted if the loss on the validation dataset does not improve for ten epochs.

A. Performance Comparison of Models

Model	Parameters in millions	F1 score	Precision	recall
InceptionV3	24	93.6	93.19	93.76
Resnet152V2	63	93.23	92.69	93.1
CNN (base)	0.653	-	-	-

Table 7.3.1 Performance matric of all models

For 10 epochs

Model	Accuracy
InceptionV3	84
Resnet152V2	97.54
CNN (base)	94.04

Table 7.3.2 Comparison of accuracy of all models

V. CONCLUSIONS

In this study convolutional neural network is used to detect and classify plant diseases. The Network was trained using the images taken in the controlled environment and achieved 94.04% on plain CNN and 97.54% on Resnet152v2 classification ability. This shows the promising ability of CNN to extract important features in the natural environment which is required for plant disease classification.and evaluates a multi-plant diagnosis technique that has been verified using several image classifier baselines. To precisely train and test our strategy, we used a transfer learning system. Additionally, we test the design using a dataset made up of 38 different classes and 14 different plant species. We find that the performance of multi-label plant disease detection can be greatly enhanced using separable convolution and skip connections.

The experiments also show that applying data augmentation on the training set improves the performance of the network when the dataset is very small.

In this study the data sample in each class is unbalanced, 3. For future work, deep learning methods to solve sample imbalance will be implemented [29]. [28] suggested the use of batch normalization to speed up the training process and boost accuracy, therefore we will also investigate batch normalization in the future.

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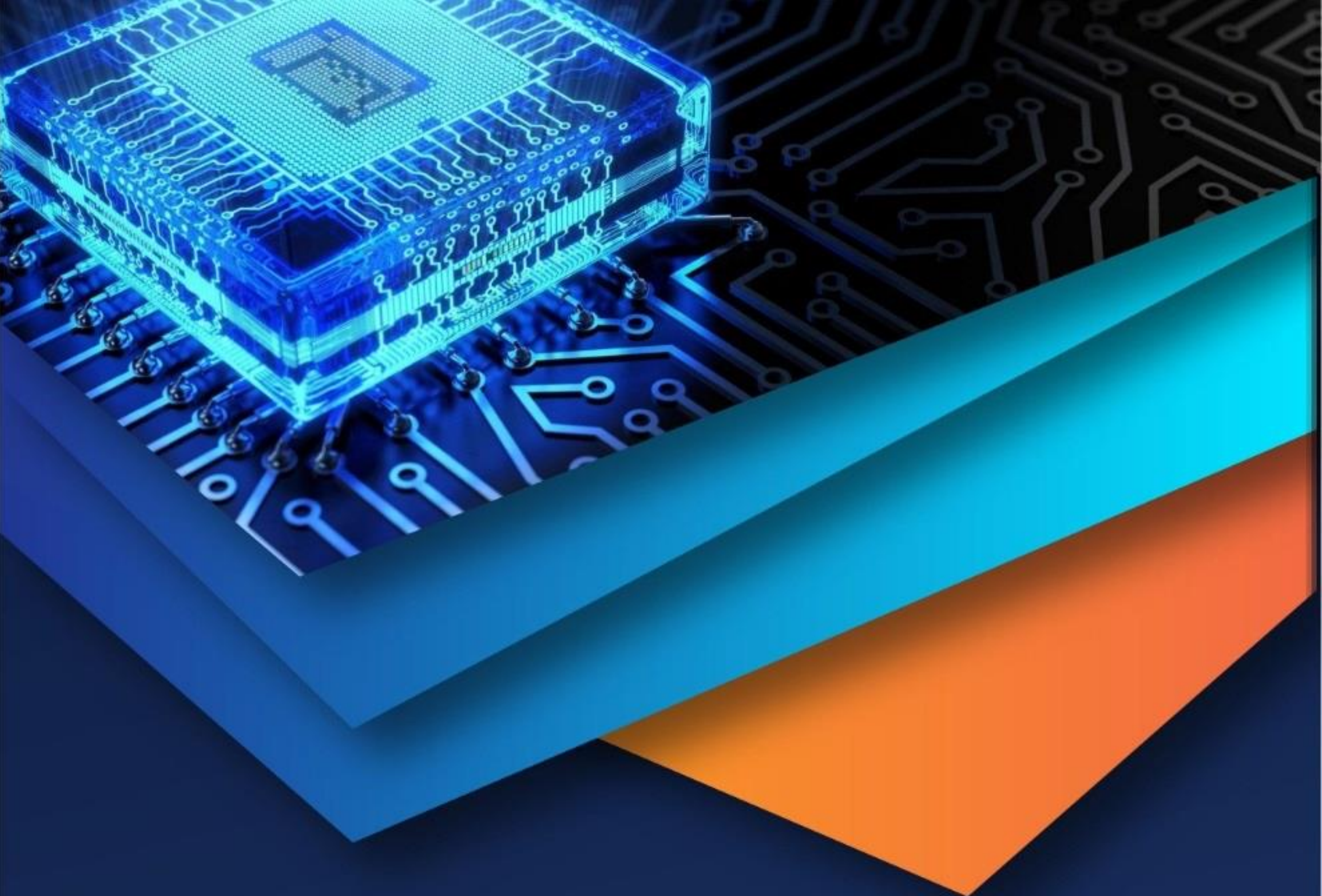

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