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Research Article

ResNet for Leaf-based Disease Classification in Strawberry Plant

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ABSTRACT

In the era of the 21st century, Deep CNN has proven its potential in crop and fruit disease classification and detection. Diseases have a ruinous effect on the quality and gross production of yields, which is related to the world economy. Proper identification of diseases at early stages may save yields from damage. CNN-based disease identification can detect the disease at the actual extent at a low cost with minimum expert manpower and labor. Strawberry is considered a functional food, that has a lot of health benefits for the human body. In this study, pre-trained weight ResNet models ResNet50, ResNet101, and ResNet152 architectures are used via the transfer learning features of CNN. Only the classifier of the models is getting updated during training. The Strawberry leaf images are used in this study from the PlantVillage dataset where both classes are balanced in terms of the number of images in each class. Among the three ResNet architectures, ResNet50 outperforms the other ResNet models achieving 88% classification accuracy during the testing period. The ResNet101 and ResNet152 models show 82% and 80% accuracy during the testing period, respectively.

1. Introduction

Agriculture has become one of the major sources of economic growth worldwide. The farmers consider several dominating factors like field soil type, weather conditions, and economic values in crop selection. The world population is rising drastically, and it is projected that the total population will reach 9.1 billion by the year 2050. An increase of 70% in yield production is required to feed the large volume of humans [1]. Plant disease damages the plant's leaves, crops, fruits, roots, and stems and eventually affects the total productivity of yields. A significant amount of yield is wasted due to plant disease which is responsible for food shortages and price hikes [2]. Usually, there are several dominating factors are involved in plant and leaf diseases.

Those factors can be grouped broadly into two categories: Biotic factors and Abiotic factors. Biotic factors are bacteria, weeds, pests, and viruses, and liable for biotic disease in plants.

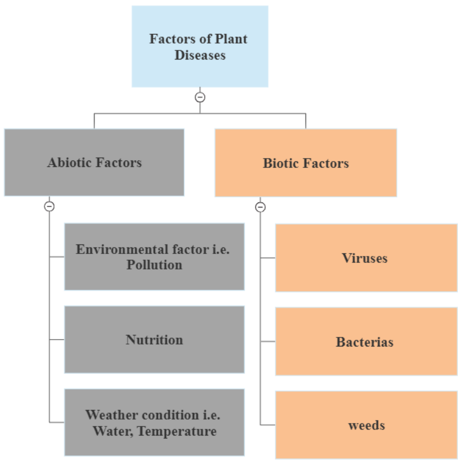

Figure 1. Significant factors for plant diseases [3].

On the other hand, Abiotic factors are environmental issues, weather, and nutrition are responsible for abiotic diseases in

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plants [3]. Significant factors for plant disease are summarized in Figure 1.

Strawberries have gained significant eminence among consumed fruits worldwide in fresh and frozen forms. Additionally, Strawberries are commercially available in processed form, for example, jams, jelly, juices, etc [4]. Nowadays, it is treated as functional food offering various potential health benefits, such as antioxidants, boosting human immunity, improving cardiovascular health, anti-inflammatory properties, anti-microbial, great for the nervous system, adjusting blood pressure, anticancer, and good for eyes, hair, and skin [5]. So, there are numerous health benefits of taking strawberries as food. The potential benefits to the human body due to consuming strawberries are summarized in Figure 2.

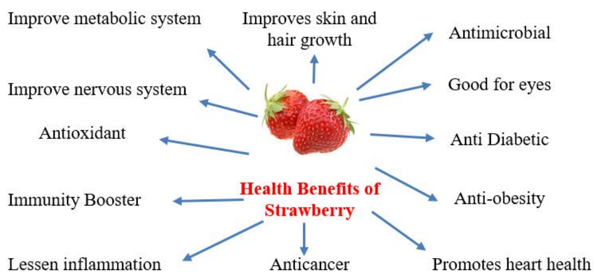


Figure 2. Noteworthy health benefits of strawberries in the human body [4].

Precision Agriculture (PA) is a modern farming system where various sophisticated technological methods and tools are used to ensure optimized yield production. Currently, precision farming is widely used in several wings of the agricultural sector, especially plant and leaf disease detection, and classification. Plant leaves and crop disease damage the yield and eventually have an adverse effect on total economic growth. Therefore, plant disease severity detection and categorization as early as possible is a vital step in precision farming [6]. Twenty-first-century technologies, for example, deep learning (DL) have proved their greatness in precision agriculture. In deep learning, a convolutional neural network (CNN) is used widely in plant disease detection and classification at early stages because CNN has the ability to extract important features automatically. That's why CNN performs better than traditional machine learning methods. Automatic disease detection and classification solve the problems with the manual system [7]. A computerized disease detection system is capable of identifying disease accurately at an early stage and it saves time.

The rest of the study is organized as follows. In section 2, the details about the literature reviews are placed. Methodology and experimental work are described in section 3. In section 4, the result and discussion are summarized following a conclusion and future work.

2. Background Study

Numerous machine learning and deep learning-based methods are proposed by a lot of researchers worldwide and achieved optimized performances and plant disease detection and classification become a famous research area in the application of deep learning in plant disease identification and categorization [8] [9]. Deep learning, more especially, CNN is efficient and effective in the various research areas of the agricultural sector because of the more optimistic outcome at a low effort and is used extensively by more and more researchers worldwide. In CNN, the important features are not chosen manually by an expert, but also extracted and selected automatically by the network from huge training data. CNN has proven its superiority among other methods in classifying and detecting plant disease [10]. Current CNN-based research is using more accurate classifiers than previous traditional machine learning classifiers [11][12]. The literature review shows that there are various award-winning CNN models proposed by renowned scientists and researchers in classification and detection tasks. Some of them are LeNet-5 [13], AlexNet [14], VGGNet [15], GoogLeNet [16], ResNet [17], DenseNet [18], ExceptionNet [19], and MobileNet [20].

Two recent review papers [21][22] summarize various deep learning methods for plant disease detection and classification with available public datasets, performance measuring metrics, current research trends, and future research directions with guidelines. A CNN-based ResNet50 model has been proposed for five types of strawberry disease detection [23]. The highest 98.06% and 99.60% accuracy were achieved during the training period using original and feature image datasets, respectively. In literature [24], CNN models were developed for the detection of 58 different disease types of 25 different plants. Those models were trained with a public dataset that contains 88,848 images and the best result hit 99.53% accuracy in disease detection. The authors in [25] used six deep learning-based algorithms in their study where powdery mildew was detected using RGB images of strawberry leaves. ResNet50 provides the best classification accuracy of 98.11% among others, for example, AlexNet, GoogLeNet, SqueezeNet, SqueezeNet-MOD1, and SqueezeNet-MOD2. AlexNet was the best in terms of processing time and SqueezeNet-MOD2 was recommended in terms of hardware limitations. In [26], the CNN-based deep learning model was applied to classify six types of strawberry plant disease with 63.7% accuracy. Their custom dataset contains 4663 strawberry leaf images and was collected locally. The dataset includes six groups including healthy class: Red spot disease, Late blight, Leaf blight, Tip burn, and Virus mosaic.

3. Methodology and Experimental Work

The convolutional neural network (CNN) model is used in this study for strawberry leaf disease classification between healthy and leaf scorch. The CNN architecture, Resnet50 is used with transfer learning the weights and then fine-tuning the model for performance comparison between two modes. The major steps of the overall procedure are shown in Figure 3.

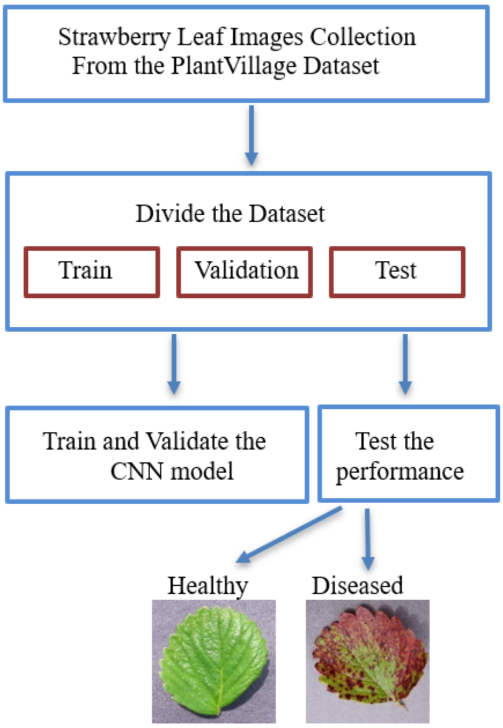


Figure 3. Major Steps in the disease classification system.

3.1 Dataset Preparation

The methodology begins with the collection of the image dataset of strawberry leaves from the dataset [27]. In this dataset, the Strawberry plant has images of only two classes: Healthy and Diseased (Leaf Scorch). Some example images from the healthy and diseased (Leaf Scroch) classes are shown in Figure 4.

Figure 4. Sample images of strawberry leaf from the PlantVillage dataset. Healthy images are shown in the first row and diseased images (Leaf Scroch) are shown in the second row.

A total of 2109 images of the strawberry plant are in the dataset where 1000 images are healthy and 1109 images are diseased. The number of images in each class is shown in Table 1.

Table 1. Images frequency in each class.

Class Names	Number of Images
Healthy	1000
Diseased (Leaf Scorch)	1109

3.2 System and Platform Specification

This experimental work was carried out on a Lenovo Thinkpad Mobile Workstation with Windows 10, 12th Generation Intel Core i7-1260P Processor, 1T SSD, RAM 32 GB, and NVIDIA Quadro T550 4GB GDDR6. Anaconda with Python version 3.9 is used as a platform and Spyder as an IDE.

3.3 Used CNN architecture

The residual neural network [17] is known as Resnet, which is a CNN architecture used in many real-life computer vision applications. It is a deep learning (DL) model that allows thousands of convolutional layers. Older CNN architectures, like VGGNet, do not cope with a large number of convolutional layers, which limits the models' performances. However, the 'vanishing gradient' problem arises upon adding more layers to the network. The residual network provides a revolutionary solution known as "skip connections" to the 'vanishing gradient' problem. These skipping connections compress the network into fewer layers that speed up the initial training of the model. ResNet launches a new concept called 'residual block' which is an important part of this network. The image in Figure 5 shows a typical residual block.

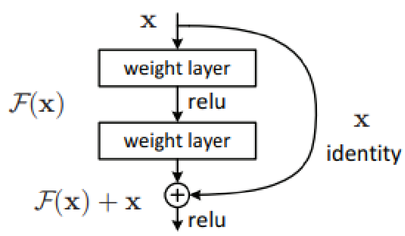


Figure 5. Residual building block [17].

This is a very popular technique of adding the input of the previous layer to the output of the next layer and has been used by many other CNN architectures.

3.3.1 ResNet Variations

Residual networks have many variations that have different numbers of layers, but the concepts are the same. ResNet50 is a variant that works with 50 neural network layers. Large Residual networks ResNet101 and ResNet152 work with

101 and 152 layers, respectively. These networks have much less complexity, although the depth of the network has increased. These three variants of ResNet architectures are used in this study via transfer learning. The total number of parameters, trainable parameters, and non-trainable parameters are listed in Table 2.

Table 2. Different types of parameters of three ResNet variants

ResNet Variants	Total Parameters	Trainable Parameters	Non-trainable Parameters
ResNet50	29,900,482	1,312,770	23,587,712
ResNet101	43,970,946	1,312,770	42,658,176
ResNet152	59,683,714	1,312,770	58,370,944

3.3.2 Design ResNet Transfer Learning

Nowadays, Image classification has been advancing notably and being popular among deep learning researchers. This is because of the availability of CNNs and large-scale public datasets. Transfer learning is a popular method in CNN where the pre-trained weights are transferred to another similar domain [28] with a lack of data and processing power. The transfer learning concept is presented diagrammatically in Figure 7.

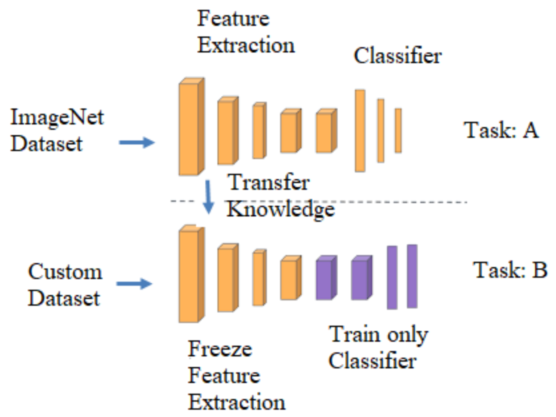


Figure 6. Concept of transfer learning.

In this work, we used the pre-trained weight of three ResNet variants: ResNet50, ResNet101, and ResNet152 to solve our problem. These variants are originally trained on the ImageNet dataset, which is more than one million images of a thousand classes. We add one global average pooling and three dense layers. Rectified linear units and sigmoid functions are used as activation functions.

3.4 Training and Evaluation of Models

To perform the classification of diseased images and healthy images, three variants of the residual neural network are used via transfer learning. Before starting to train the models, we divide the images dataset randomly into training, validation, and testing parts using the sklearn built-in function train_test_split. The dataset is partitioned at the run time and after partitioning the dataset, the number of images in each set is shown in Figure 8.

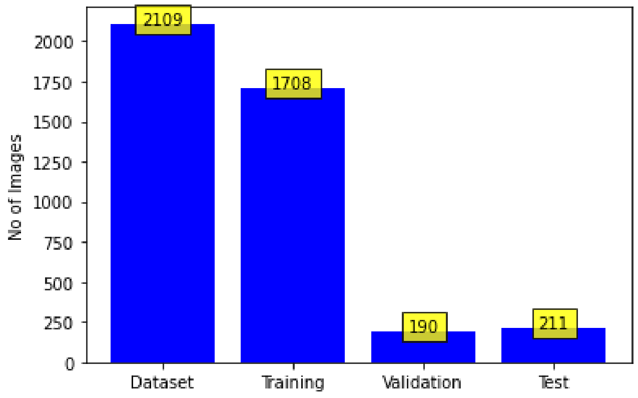


Figure 7. Number of images in training, validation, and test set.

All the top layers of the models are frozen during the training period which means the weights are not updated accordingly. Only the fully connected layers are updated and trained during the training period using the training image set. The models are trained and validated at each epoch of a total of 60 epochs using the fit() function. In training and validation time, the following parameters are used in the models-

- Number of Epochs: 60
- Optimizer: Adam
- Learning rate: 0.001
- Loss Function: Sparse Categorical Crossentrophy
- Batch size: 32
- Number of Class: 2 (binary)
- Activation Function: ReLU and Sigmoid

At training time, the Adam optimizer is used with a default learning rate of 0.001 value. Adam optimizer is considered the default optimizer in CNN because of its unparallel features. To track loss in validation, 'sparse_categorical_crossentrophy' is used as a loss function, and 'accuracy' to track accuracy. At the last fully connected layer, the 'sigmoid' function is used as an activation function to meet the requirement for performing binary classification.

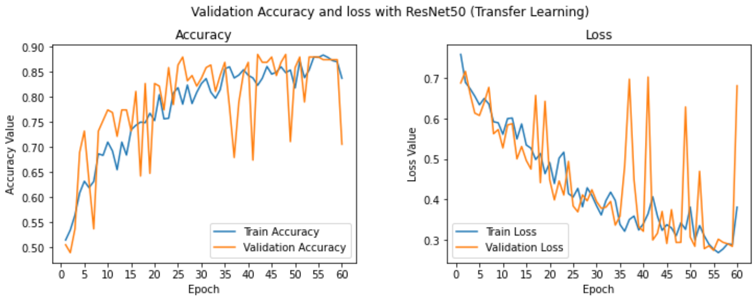
4. Result and Discussion

To find out the prediction abilities of the ResNet models, that has been trained and validated in training and validation period. The model's performances are evaluated using test image set that are unknown to the models. Classification report and confusion matrix are generated with the help of *sklearn.metrics.* The classification report is shown in Table 3. An satisfactory result was achieved by ResNet50 which is 88% classification accuracy on the test dataset. An 82% and 80% accuracy is achieved by ResNet101 and ResNet152

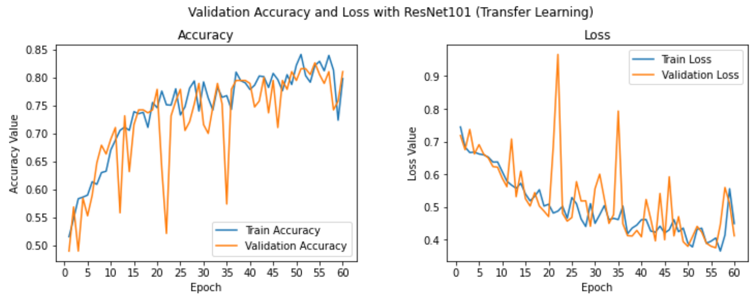
Table 3. Classification report on test dataset.

Models	Accuracy	Precision	Recall	F1 Score
ResNet50	88%	88%	87%	88%
ResNet101	82%	81%	85%	83%
ResNet152	80%	72%	100%	83%

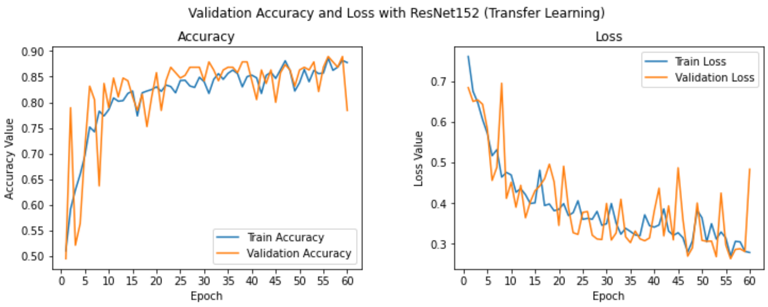
architecture, respectively. The highest 88% precision and F1 score are shown by ResNet50 and 100% recall is shown by ResNet152. The validation accuracy and loss graph are described in Figure 8.



(a) ResNet50



(b) ResNet101



(c) ResNet152

Figure 8. Validation accuracy and loss graph.

The confusion matrix is used to describe the performance of classification work. The confusion matrix is shown in Figure 9, Figure 10, and Figure 11, where images with leaf scorch are considered diseased, and images with no abnormalities are considered healthy. ResNet50 model outperforms others. This ResNet variant correctly identifies 93 healthy images out of 105 images and 93 diseased images out of 106 images. This Model predicts wrongly 12 and 14 cases in the healthy and diseased classes, respectively. The Resnet152 model predicts 100% sample correctly on the diseased class but shows the worse result in the healthy class where it identifies only 63 images correctly out of 105 images. In the case of the healthy class, the ResNet101 model identifies 84 images correctly and 21 images wrongly. On contrary, 90 diseased images are predicted correctly out of 106 images.

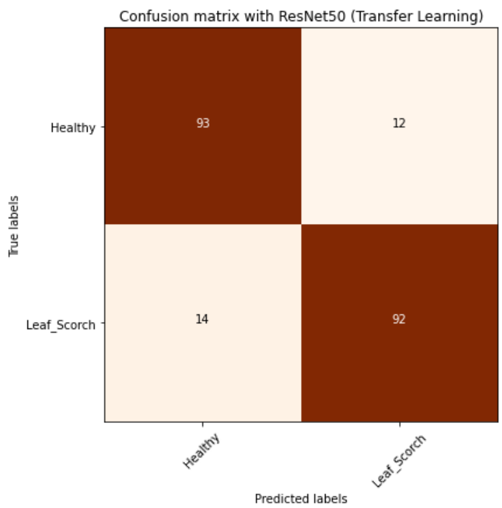


Figure 9. Confusion matrix for ResNet50 model.

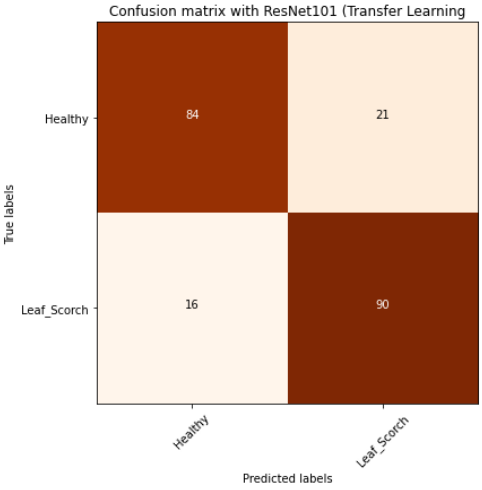


Figure 10. Confusion matrix for ResNet101 model.

The ResNet101 model predicts 16 diseased images as a healthy class out of 106 images and 21 healthy images as a diseased class out of 105 images.

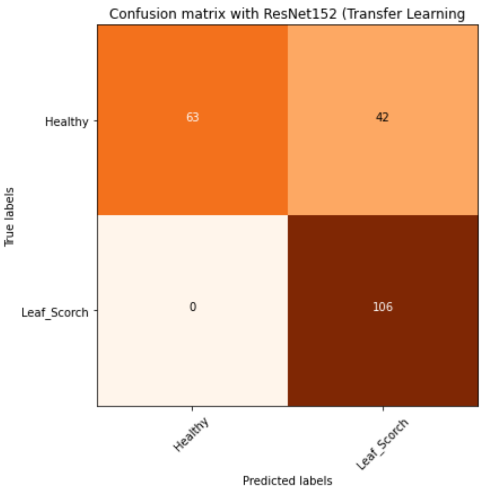


Figure 11. Confusion matrix for ResNet152 model.

As a whole, ResNet152 achieved the best result in the diseased class and ResNet50 achieved the best result in the healthy class.

5. Conclusion and Future work

CNN is best suited for image recognition because of its ability to reduce the high dimensionality of images without destroying any information. Moreover, CNN automatically learns features from images without any human intervention and that's why it achieved higher performance as compared to other neural networks and traditional image processing algorithms. Therefore, CNN is extensively used in various plant disease classification and detection research by the research community and shows significant advancement. In this paper, the strawberry leaf disease classification based on leaf images was performed using three variants of residual networks i.e., ResNet50, ResNet101, and ResNet152. A total of 2109 images were used form the PlantVillage dataset in this research where the training set contains 1708 images, the validation set contains 190 images, and the testing set contains 211 images. The best 88% classification accuracy was achieved by ResNet50 in testing as compared to others ResNet variants. Overall, ResNet50 shows the best performance in classifying healthy class and ResNet152 shows the best performance in classifying disease class. In the future, we will verify other pretrained CNN models with transfer learning, fine-tuning, and hyperparameter tuning to refine the result of leaf disease classification in the strawberry plant.

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