Plant Leaves Diseases Detection Using Convolutional Neural Network

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **"Plant Leaves Diseases Detection Using Convolutional Neural Network"**, submitted by **Protyasha Ghosh**, ID No: **191-15-12853** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on January 28th, 2023.

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We hereby declare that, this project has been done by us under the supervision of **Md. Sazzadur Ahamed, Assistant Professor and Department of CSE** at Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

In agriculture technologies, images are a key source of data and information. The examination of smart farms was significantly impacted by the usage of image processing methods. The analytical method that uses digital image processing would categorize the indications of having diseases and which diseases the plants are suffering from far earlier than a human could. As a result the farmers will be able to take corrective actions timely. The study presents some visualization techniques used for detecting diseases from the collected images. To achieve the best result in diseases detection image processing techniques go through a number of stages including picture acquisition, image augmentation, image segmentation and feature extraction. In this analysis it has been demonstrated that image processing technology can aid in the growth of agricultural automation to achieve the benefits of cheap cost, high efficiency, and high accuracy.

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INTRODUCTION

1.1 Introduction

Bangladesh is an agricultural nation. Agriculture is its key economic driver. Agriculture in Bangladesh faces a serious threat from crop loss caused by diseases. In Bangladesh, more than 454 illnesses have so far been identified in about 100 farmed crops (Anon., 2006). Crops suffer severe losses as a result of the illnesses. The nation's overall yield output is hampered by these large losses. The condition often causes a 30–50% loss (Khan, 1999).

Phomopsis vexans causes major fruit rots in eggplant, causing 15-20% of cases in general and 30-50% of severe cases (Das, 1998; Khan, 1999); this disease costs roughly 80 million taka (Anon., 2003). Crop damage may therefore lead to unforeseen losses that harm the farming sectors' production, which will have an impact on the economy. As a result, maintaining good agricultural practices and ensuring effective output together with high profits depend on taking care of the plants.

Plants are particularly susceptible to infections since their leaves are where the disease symptoms initially show themselves. Farmers should think about keeping an eye on their crops so they can minimize losses since plant diseases have negative effects on both the economy and the environment. The monitoring of crops with the unaided eye is a method that specialists employ to keep a check on the crops. This is a classic approach that comes with a lot of time-related limitations because monitoring operations are carried out manually and specialists are present. However, crop monitoring is currently being developed to be digital and semi-automatic, meaning that merely from the symptoms that are presented on the leaf, the disease might be detected in an easier, quicker, and less expensive manner. Because most farmers lack the necessary background and expertise about monitoring the crops and dealing with illnesses, this digitalized technique will also be advantageous for farmers as it will make it easier for them to spot problems. Farmers might utilize the recommended technique we present in this study to boost production without the need to consult professionals. The primary goal of this suggested system is not just to identify plant diseases utilizing image processing technologies. The most recent technologies, namely image processing, have been involved in the digitization of the agricultural sector. As a result, we use Tensorflow as an image processing technique to create our system, which is intended to be automated.

1.2 Motivation

The advancement of image processing and its success in other areas have made it feasible for it to be utilized in agriculture. To address the majority of practical issues in the agricultural industry, subject matter experts' counsel is constantly required. It is more time-consuming, more expensive, and unaffordable. The agriculture industry has started collaborating with cutting-edge information technology employing methods like image processing as a result of the better success rate in other industries. For the input picture obtained using any imaging technique, these approaches generate an output. Farmers, agro-based businesses, and marketers may benefit from and learn from the findings. It offers cost-effective decision help in a timely manner.

1.3 Objectives

Our main objective is to design such a model which can detect leaf diseases. The farmers will be able to take the appropriate action to combat the illnesses and prevent loss if we can identify crop leaf diseases early on, which is our key goal.

1.4 Expected Outcomes

In this study I have built a CNN (Convolutional Neural Network) model to detect the leaf diseases. Here I have worked with 5 types of plant (corn, bell pepper, grape, cherry, strawberry) leaves with almost 13 diseases (classes). I start by separating the training and testing models. Each class of the trained model was evaluated separately, and tests were run on each picture in the validation set.

1.5 Research Questions

The following is a list of the primary questions that are the subject of this research:

- What aspects should be taken as parameters to predict the diseases of the plants earlier?
- Which algorithm would be the best solution for this problem statement?
- How to process such vast images for utilizing the algorithm?

1.5 Overview of the Paper

CHAPTER 1: Introduction (1.1 Introduction, 1.2 Motivation, 1.3 Objective, 1.4 Expected Outcome)

CHAPTER 2: Literature Review (2.1 Introduction, 2.2 Related Works, 2.3Comparative Analysis and Summary, 2.4 Scope of the Problem, 2.5 Challenges)

CHAPTER 3: Research Methodology (3.1 Introduction, 3.2 Data Collection Proceduer, 3.3Flow Diagram, 3.4 Research Analysis,)

CHAPTER 4: Impact on Society and Environment (4.1 Impact on Society, 4.2 Impact on Environment)

CHAPTER 5: Conclusion (5.1 Summary of the Study, 5.2 Conclusion 5.3 Further Implication of the Study)

CHAPTER 2
BACKGROUND

2.1 Introduction

The implementation of image processing approaches to the detection and diagnosis of leaf diseases in plants has been the subject of a sizable amount of study. A substantial amount of research is being done on a variety of topics, including feature extraction, plant macro- or micronutrient detection, fruit disease detection, and investigations in the detection of plant leaf or crop illnesses. Digital technologies have become more crucial to critical agricultural challenges during the past few years. Technical help is also needed with regard to the present situation of agriculture globally, nutrient loss, choosing the proper pesticides, and early identification of plant/leaf diseases. To reach a decision, methods for predicting are combined with methods for identifying trend patterns and choosing characteristics. Among all the effort, my study is also a pretty tiny venture.

2.2 Related Works

Numerous research have been done to develop methods that can help identify crops in an agricultural setting in order to discover the best solution to the problem of crop disease detection. The most current investigations on CNN's applicability in the larger field of agriculture are presented in this part, which also include papers from peer-reviewed journals that employ CNN techniques with plant datasets.

CNN algorithms for the identification of plant diseases were examined by Abade et al. [1]. Between 2010 and 2019, 121 publications were published, which the authors examined. In this review, TensorFlow was found to be the most commonly used framework, while PlantVillage was chosen as the most frequently used dataset. The fundamental techniques of CNN models used to diagnose plant diseases using leaf pictures were described by Dhaka et al. [2]. Additionally, they contrasted frameworks, pre-processing methods, and CNN models. The study also examines the datasets and performance metrics used to judge the effectiveness of the model. A review for classifying plant diseases using a CNN was presented by Lu et al. [3]. In Agriculture 2022, 12, 1192; 3 of 21 plant diseases were classified, and they assessed the major issues and solutions of CNN utilized for these classifications. They found that further investigation using more complicated datasets was needed to produce a more desirable outcome. A review on disease detection using CNN, concentrating on potato leaf disease, was provided by Bangari et al. [4]. Convolutional neural networks are more effective at spotting the condition, they found after reviewing a number of articles. They also found that CNN made a major contribution to the highest level of illness detection accuracy. The four essential phases in this study's disease identification procedure are as follows: first, the RGB color format of the input image is converted to HSI color. After that, a threshold value is used to identify and isolate the green pixels in the image. To extract the region of interest from the image, the segmentation technique is used in the third phase. Finally, a disease is diagnosed using the classifier based on its attributes. On the 500 plant leaves from the data set, the suggested method's robustness has been proved [5]. The segmenting of the plant's diseased parts using various ways was covered in this research. The approaches for feature extraction and classification, as well as the categorization of plant diseases, were also covered in this study. SVMs, back propagation algorithms, self-organizing feature maps, and other ANN techniques may be effectively utilized to classify plant diseases [6]. Anand H. Kulkarni et al. suggested a method for early and reliable detection of plant diseases utilizing a variety of image processing techniques, where the Gabor filter was utilized for feature extraction and an ANN-based classifier was employed for classification with a recognition rate of up to 91% [8]. S. Arivazhagan, et al. have suggested employing textural characteristics to detect hazardous regions and classify them. Ten different plant species, including banana, beans, jackfruit, lemon, mango, potato, tomato, and sapota, were used to test their algorithm. Support vector machine (SVM) classifier has a 94.74% accuracy rate [8]. Based on statistical classification, Dheeb Al Bashish, et al. created a neural network classifier that could accurately identify and categorize the disorders with an accuracy of about 93%. Song Kai et al. successfully recognized the results of a research project on the picture detection of corn disease using BP networks [9].

2.3 Comparative Analysis and Summary

The discussion in Chapter 2 focuses on the earlier research that has been done in this area. Wide range of approaches for working on projects including CNN technology and image processing are discussed here, as well as a focused investigation centered on the English language.

2.4 Scope of the Problem

This paper incorporates the CNN model to identify several particular plant leaf diseases. Even though I collected the dataset in accordance with my research, it might have been clearer and more comprehensive because more define more accuracy. To preprocess the images and separate the train, test, and validation sets in accordance with that, I examined the Convolutional Neural Network model; however, alternative approaches like KNN and SVM algorithm may also be used for better results. The results would be more accurate if we had more time to do our research.

2.5 Challenges

You must always overcome obstacles in order to achieve a task. Since I've had so many difficulties, I don't make any exceptions either. In order to detect plant leaf diseases for my research, I must gather images for my dataset. The majority of the photographs in the collection, which I downloaded from the internet, are hazy and poorly defined. It was difficult to clean the photos due to this fact. I think it would have been lot better if I had been able to take the pictures by myself. To effectively use the method and improve accuracy, we must work with a large quantity of data/images, but in order to process these photos, we require sufficient hardware support, such as additional hard drive capacity to execute the epoch. In my instance, I could not work with the entire dataset I downloaded from the internet because the RAM couldn't handle such a large amount of data, thus I had to clutter most of the photographs, which reduced the prediction accuracy.

Another problem was that I didn't know much about plant diseases and the criteria used to detect them; it would have been ideal if I could have gone and spoken to farmers in person to learn more about this idea. Additionally, because I am working alone on this thesis and it is highly time-consuming, it has been a little difficult for me to complete all the tasks. Moreover, as this is my first work with image processing, learning and comprehending the methodologies was difficult yet rewarding. Despite all of these unforeseen circumstances, my supervisor, sir, assisted me with all of the requirements, and I did my absolute best to do this project properly.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

The initial objective was to create a model that farmers or agricultural experts might use to help them recognize the illnesses that the plants are experiencing. By uploading a snapshot of a sick plant leaf and receiving information on the disease's classification, the appropriate procedures may be taken sooner to get rid of it. I implemented Convolutional Neural Networking by using Tensorflow, an open source library for deep learning applications and Keras, a deep learning API for implementing neural network.

A CNN is a type of network design for deep learning algorithms that is primarily utilized for image recognition and pixel data processing applications. There are different forms of neural networks in deep learning, but CNNs are the network design of choice for identifying and recognizing things.

Keras has several neural network layers to train, such as convolution layers. There are also no-parameter-to-train layers, such as flatten layers, which turn an array, such as an image, into a vector. Keras' preprocessing layers are developed for usage in the early stages of a neural network. They can be used for picture preparation, such as resizing or rotating images, or adjusting brightness and contrast. Although the preprocessing layers are meant to be part of a bigger neural network, they may also be used as functions.

3.2 Data Collection Procedure

The dataset was collected from an open dataset called 'Plant Diseases' on Kaggle. There were information about 14 plants and 38 different diseases regarding those plants. But for my work I customized the dataset and choose 5 plants and 17 diseases specifically. There are total 4586 images belonging to 17 classes. I splited the dataset into three parts: training, testing and validation. I used 80% of the images for training the model, 10% for validation and 10% for testing respectively. The number of images in each class are given below:

Table 3.2: Image no of each class

Class	Diseases	Number of images
1	Potato Early Blight	394
2	Potato Late Blight	402
3	Potato Healthy	120
4	Corn spot gray leaf	209
5	Corn common rust	228
6	Corn healthy	213
7	Grape black rot	191
8	Grape esca black measles	183
9	Grape Leaf blight Isariopsis Leaf Spot	149
10	Grape healthy	130
11	Bell pepper bacterial spot	227
12	Bell pepper healthy	201
13	Tomato Early Blight	400
14	Tomato Late Blight	444
15	Tomato Healthy	355
16	Tomato Leaf Mold	384
17	Tomato Mosaic Virus	296
	Total	4586

Figure 3.2.2 to 3.2.14 shows some plant leaves with different diseases.

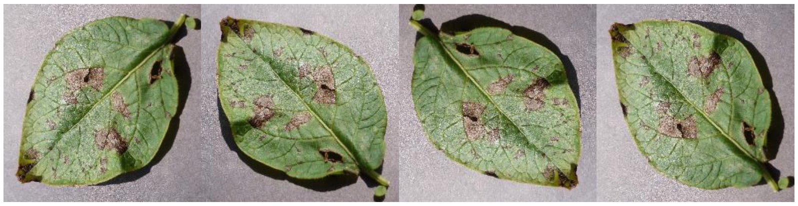

Figure3.2.2: Potato Early Blight

Figure3.2.3: Potato Late Blight

Figure3.2.4: Potato Healthy

Figure3.2.5: Tomato Early Blight

Figure3.2.6: Tomato Late Blight

Figure3.2.7: Tomato Healthy

Figure3.2.8: Tomato Leaf Mold

Figure3.2.9: Tomato Mosaic Virus

Figure3.2.10: Grape Black Rot

Figure3.2.11: Grape Esca Black Measles

Figure3.2.12: Grape Leaf blight Isariopsis Leaf Spot

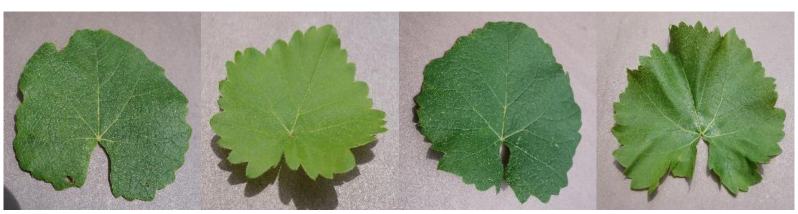

Figure3.2.13: Grape Healthy

Figure3.2.14: Corn Healthy

Figure3.2.15: Corn Spot Gray Leaf

Figure3.2.16: Corn Common Rust

Figure3.2.17: Bell Pepper Healthy

Figure3.2.18: Bell Pepper Bacterial Spot

3.3 Data Preprocessing

For preprocessing the image dataset I converted the images into Numpy array. Keras dataset preparation facilities, found at tf.keras.preprocessing, assist in converting raw disk data to a tf.data. A dataset is a collection of data that may be used to train a model. Then run image dataset from directory (main directory, labels='name') to get a tf.data. Dataset containing batches of images from the subdirectories class_a and class_b, as well as the labels 0 and 1 (0 for class a and 1 for class b).

3.4 Flow Diagram

The proposed methodology for identifying plant leaf diseases is shown in flow diagram form in Figure 3.3.1. It is divided into many stages, including pre-processing, feature extraction, prediction, and charting the pathogen area. The CNN architecture uses a layered method where each layer is processed in turn.

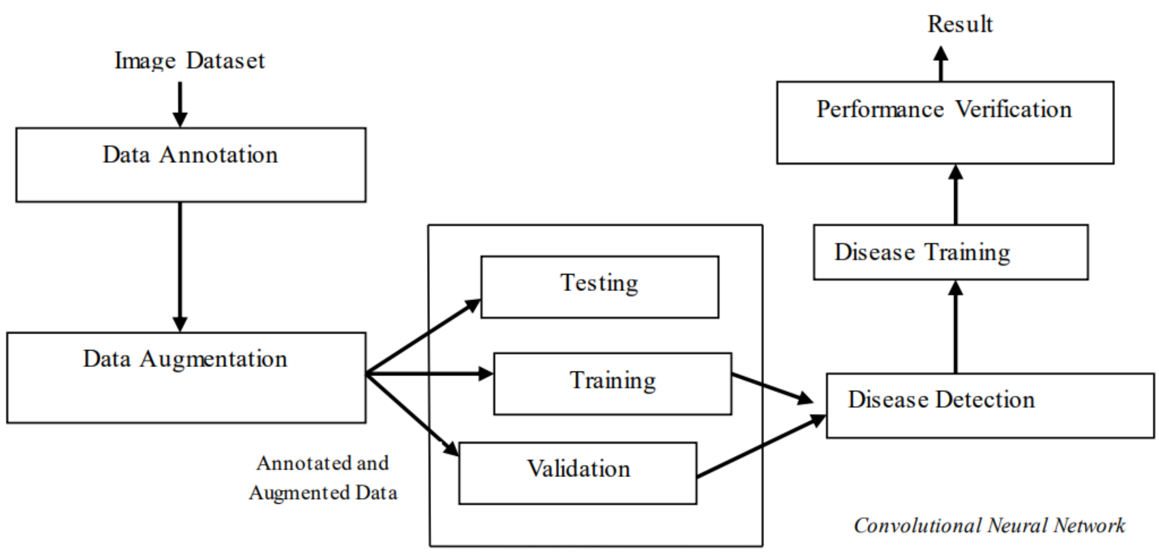

Figure3.4: Proposed methodology

3.5 Implementation

3.5.1 Visualize some of the images from my dataset

It is necessary to view the augmentation outcome so that it can be confirmed that the augmentation result is what I desire. You can do this with matplotlib. To display an image, I used the imshow() function in matplotlib. However, in order for the picture to be properly shown, it should be provided as an array of 8-bit unsigned integers (uint8).

Here I have built a dataset using image dataset from directory(), I get the first batch (of 32 photos) and displayed a few of them with imshow(), as seen below:

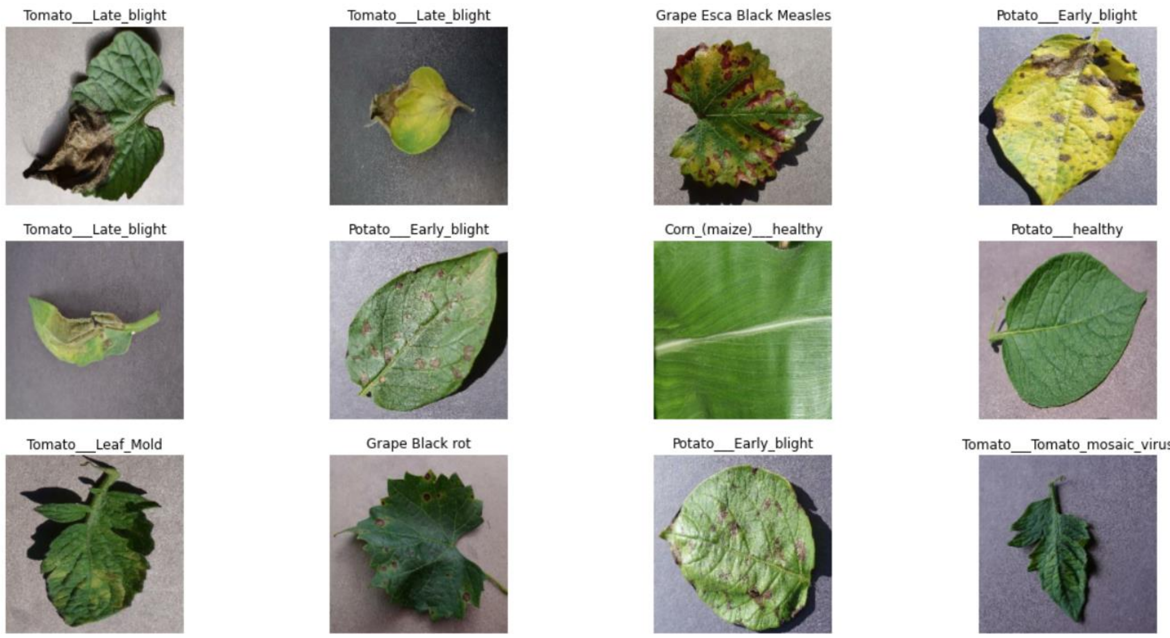

Figure3.5.1: Image Visualization from Dataset

Using ds.class names, I showed twelve photos in a grid, each labeled with its appropriate categorization label. For presentation, the photos should be transformed to a NumPy array in uint8.

3.5.2 Plotting Accuracy and Loss Curves

Accuracy vs. Loss is usually overlooked. During model training, we frequently consider and care about the accuracy metric. However, loss must be addressed in the same way.

Accuracy score is defined as the number of correct predictions obtained. Loss values are the values that indicate the deviation from the desired goal state. Accuracy - loss variation occurs when:

- Predictions are approaching the intended values. Loss values would improve but accuracy would stay same. The model is becoming more robust and accurate.
- In contrast to the preceding point, if the model is overfitting, a single incorrect prediction would result in a considerable difference in loss values with little change in accuracy values.

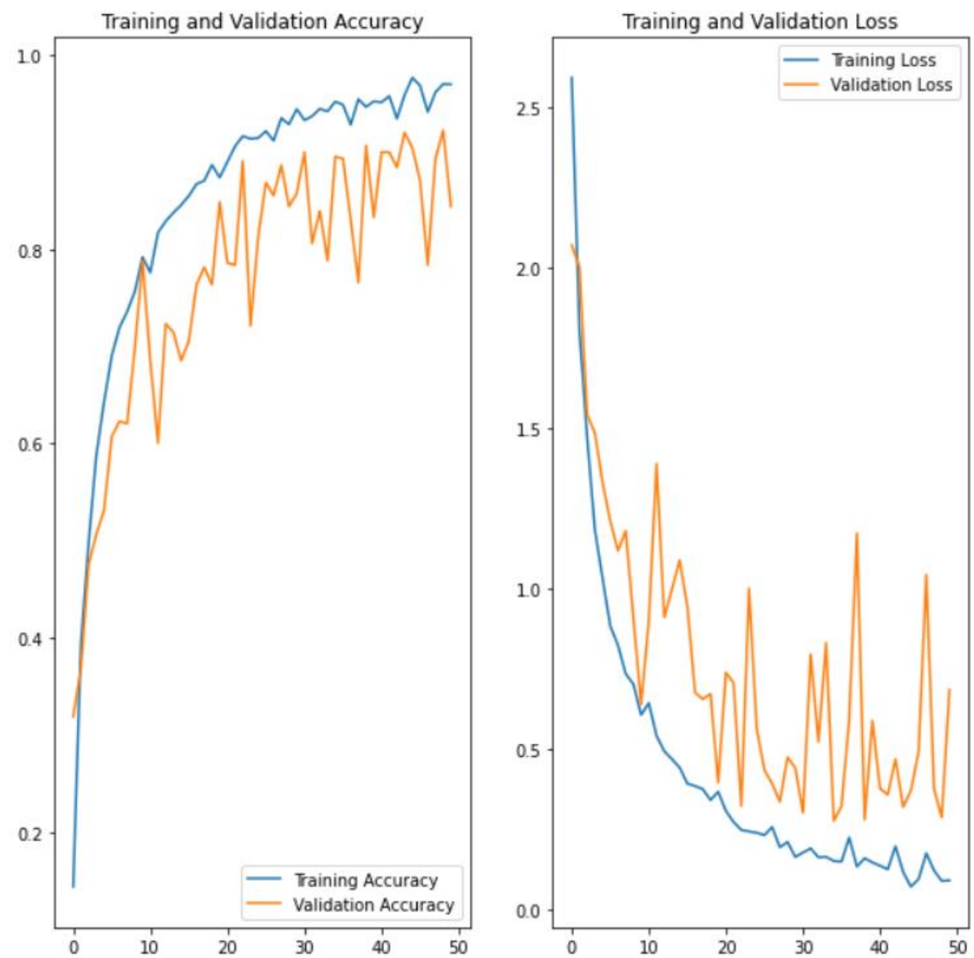

Fig.3.5.2: Accuracy and Loss Curves

Accuracy = number of correct prediction/ total number of correct prediction. For example, in this study the accuracy is 89.58%(approximately), it indicates that 89 correct predictions were made out of 100 total cases.

A loss function analyzes the target and predicted output values to determine how effectively the neural network predicts the training data. When training, we try to minimize the difference between predicted and target outputs.

3.5.3 Run Prediction on a Sample Image

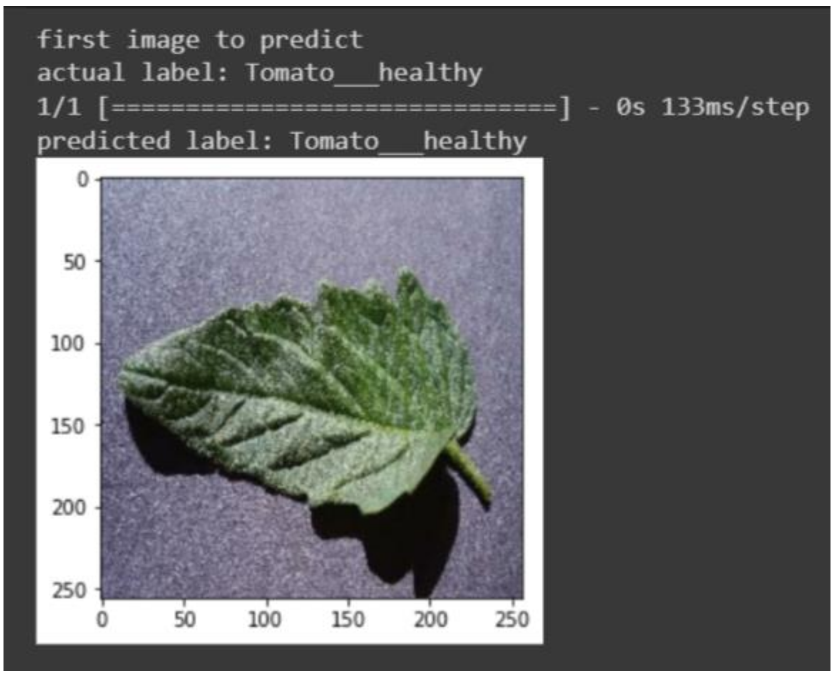

Fig.3.5.3: Run Prediction on a Sample Image

3.5.4 Run Interface on Few Sample Images

Here I displayed 9 images on a grid with the lable which shows the plant leaves diseases with the prediction of their diseases and confidence percentage.

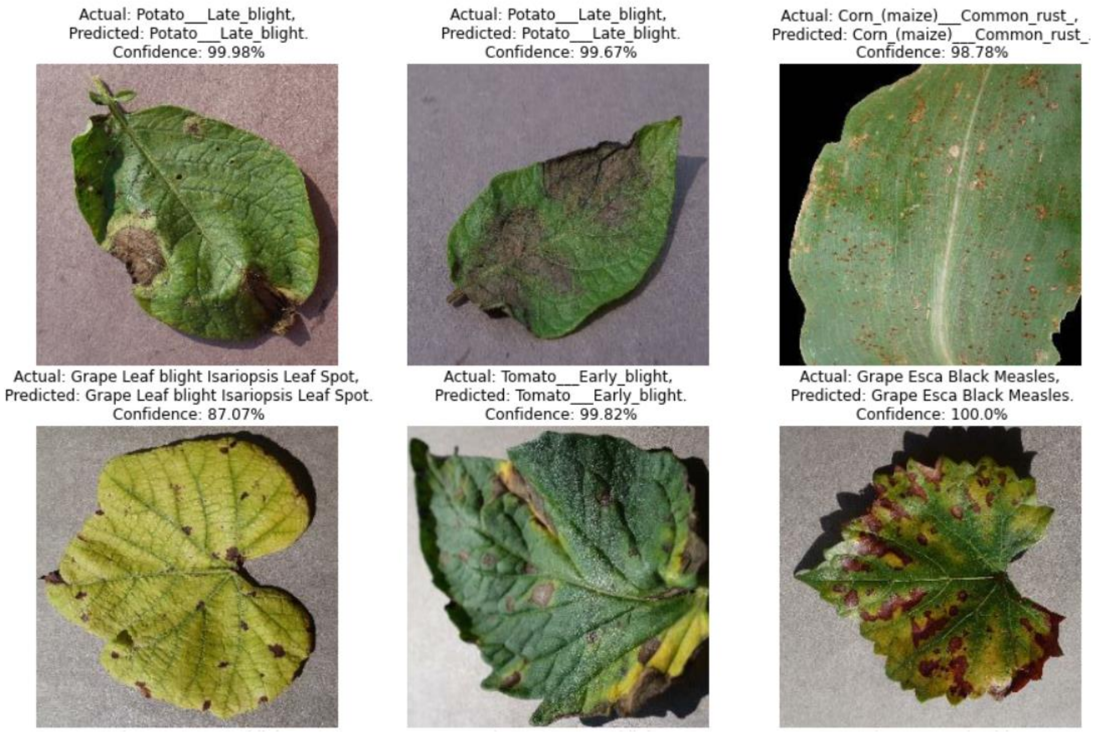

Fig.3.5.4: Run Prediction on Few Sample Images (1)

Fig.3.5.5: Run Prediction on Few Sample Images (2)

3.5.5 The proposed model with accuracy and loss for 50 epochs

An epoch is defined as the total number of iterations of all the training data in one cycle for training the machine learning model when all of the training data is used at once.

```
Epoch 1/50
115/115 [==============================] - 1363s 361ms/step - loss: 2.5914 - accuracy: 0.1443 - val_loss: 2.0692 - val_accuracy: 0.3192
Epoch 2/50
115/115 [==============================] - 33s 289ms/step - loss: 1.8008 - accuracy: 0.3937 - val_loss: 2.0010 - val_accuracy: 0.3683
Epoch 3/50
115/115 [==============================] - 33s 287ms/step - loss: 1.4690 - accuracy: 0.4978 - val_loss: 1.5402 - val_accuracy: 0.4754
Epoch 4/50
115/115 [==============================] - 33s 288ms/step - loss: 1.1817 - accuracy: 0.5878 - val_loss: 1.4843 - val_accuracy: 0.5067
Epoch 5/50
115/115 [==============================] - 33s 288ms/step - loss: 1.0298 - accuracy: 0.6427 - val_loss: 1.3293 - val_accuracy: 0.5312
Epoch 6/50
115/115 [==============================] - 34s 294ms/step - loss: 0.8815 - accuracy: 0.6903 - val_loss: 1.2090 - val_accuracy: 0.6071
Epoch 7/50
115/115 [==============================] - 33s 288ms/step - loss: 0.8213 - accuracy: 0.7192 - val_loss: 1.1160 - val_accuracy: 0.6228
Epoch 8/50
115/115 [==============================] - 33s 287ms/step - loss: 0.7329 - accuracy: 0.7356 - val_loss: 1.1781 - val_accuracy: 0.6205
Epoch 9/50
115/115 [==============================] - 33s 288ms/step - loss: 0.6999 - accuracy: 0.7564 - val_loss: 0.9067 - val_accuracy: 0.6987
Epoch 10/50
115/115 [==============================] - 33s 288ms/step - loss: 0.6042 - accuracy: 0.7917 - val_loss: 0.6376 - val_accuracy: 0.7879
Epoch 11/50
115/115 [==============================] - 33s 290ms/step - loss: 0.6413 - accuracy: 0.7758 - val_loss: 0.8981 - val_accuracy: 0.6853
Epoch 12/50
115/115 [==============================] - 34s 297ms/step - loss: 0.5393 - accuracy: 0.8168 - val_loss: 1.3873 - val_accuracy: 0.6004
Epoch 13/50
115/115 [==============================] - 33s 290ms/step - loss: 0.4913 - accuracy: 0.8286 - val_loss: 0.9085 - val_accuracy: 0.7232
Epoch 14/50
115/115 [==============================] - 33s 289ms/step - loss: 0.4664 - accuracy: 0.8373 - val_loss: 0.9959 - val_accuracy: 0.7143
Epoch 15/50
115/115 [==============================] - 33s 291ms/step - loss: 0.4400 - accuracy: 0.8453 - val_loss: 1.0865 - val_accuracy: 0.6853
Epoch 16/50
115/115 [==============================] - 33s 291ms/step - loss: 0.3903 - accuracy: 0.8546 - val_loss: 0.9421 - val_accuracy: 0.7054
Epoch 17/50
115/115 [==============================] - 34s 295ms/step - loss: 0.3825 - accuracy: 0.8669 - val_loss: 0.6740 - val_accuracy: 0.7634
Epoch 18/50
```

Fig.3.5.6: Accuracy and loss for 50 epochs (1)

```
Epoch 19/50
115/115 [==============================] - 33s 288ms/step - loss: 0.3387 - accuracy: 0.8866 - val_loss: 0.6702 - val_accuracy: 0.7634
Epoch 20/50
115/115 [==============================] - 33s 288ms/step - loss: 0.3648 - accuracy: 0.8734 - val_loss: 0.3938 - val_accuracy: 0.8482
Epoch 21/50
115/115 [==============================] - 33s 289ms/step - loss: 0.3050 - accuracy: 0.8896 - val_loss: 0.7368 - val_accuracy: 0.7857
Epoch 22/50
115/115 [==============================] - 34s 296ms/step - loss: 0.2702 - accuracy: 0.9057 - val_loss: 0.7039 - val_accuracy: 0.7835
Epoch 23/50
115/115 [==============================] - 33s 289ms/step - loss: 0.2456 - accuracy: 0.9161 - val_loss: 0.3200 - val_accuracy: 0.8906
Epoch 24/50
115/115 [==============================] - 33s 287ms/step - loss: 0.2410 - accuracy: 0.9133 - val_loss: 0.9987 - val_accuracy: 0.7210
Epoch 25/50
115/115 [==============================] - 33s 289ms/step - loss: 0.2368 - accuracy: 0.9142 - val_loss: 0.5616 - val_accuracy: 0.8125
Epoch 26/50
115/115 [==============================] - 33s 287ms/step - loss: 0.2294 - accuracy: 0.9213 - val_loss: 0.4323 - val_accuracy: 0.8683
Epoch 27/50
115/115 [==============================] - 33s 288ms/step - loss: 0.2548 - accuracy: 0.9114 - val_loss: 0.3899 - val_accuracy: 0.8549
Epoch 28/50
115/115 [==============================] - 34s 292ms/step - loss: 0.1914 - accuracy: 0.9347 - val_loss: 0.3336 - val_accuracy: 0.8862
Epoch 29/50
115/115 [==============================] - 33s 288ms/step - loss: 0.2082 - accuracy: 0.9281 - val_loss: 0.4723 - val_accuracy: 0.8438
Epoch 30/50
115/115 [==============================] - 33s 287ms/step - loss: 0.1613 - accuracy: 0.9440 - val_loss: 0.4390 - val_accuracy: 0.8571
Epoch 31/50
115/115 [==============================] - 33s 288ms/step - loss: 0.1750 - accuracy: 0.9325 - val_loss: 0.2994 - val_accuracy: 0.8996
Epoch 32/50
115/115 [==============================] - 33s 289ms/step - loss: 0.1881 - accuracy: 0.9366 - val_loss: 0.7936 - val_accuracy: 0.8058
Epoch 33/50
115/115 [==============================] - 34s 293ms/step - loss: 0.1600 - accuracy: 0.9442 - val_loss: 0.5197 - val_accuracy: 0.8393
Epoch 34/50
115/115 [==============================] - 33s 289ms/step - loss: 0.1618 - accuracy: 0.9415 - val_loss: 0.8290 - val_accuracy: 0.7879
Epoch 35/50
115/115 [==============================] - 33s 287ms/step - loss: 0.1486 - accuracy: 0.9516 - val_loss: 0.2738 - val_accuracy: 0.8951
Epoch 36/50
115/115 [==============================] - 33s 289ms/step - loss: 0.1470 - accuracy: 0.9483 - val_loss: 0.3195 - val_accuracy: 0.8929
```

Fig.3.5.7: Accuracy and loss for 50 epochs (2)

```
Epoch 37/50
115/115 [==============================] - 33s 286ms/step - loss: 0.2220 - accuracy: 0.9278 - val_loss: 0.5914 - val_accuracy: 0.8304
Epoch 38/50
115/115 [==============================] - 34s 295ms/step - loss: 0.1311 - accuracy: 0.9541 - val_loss: 1.1707 - val_accuracy: 0.7656
Epoch 39/50
115/115 [==============================] - 33s 288ms/step - loss: 0.1576 - accuracy: 0.9461 - val_loss: 0.2773 - val_accuracy: 0.9062
Epoch 40/50
115/115 [==============================] - 33s 288ms/step - loss: 0.1442 - accuracy: 0.9519 - val_loss: 0.5867 - val_accuracy: 0.8326
Epoch 41/50
115/115 [==============================] - 33s 289ms/step - loss: 0.1342 - accuracy: 0.9508 - val_loss: 0.3747 - val_accuracy: 0.8996
Epoch 42/50
115/115 [==============================] - 33s 287ms/step - loss: 0.1228 - accuracy: 0.9574 - val_loss: 0.3553 - val_accuracy: 0.8996
Epoch 43/50
115/115 [==============================] - 34s 294ms/step - loss: 0.1947 - accuracy: 0.9341 - val_loss: 0.4664 - val_accuracy: 0.8839
Epoch 44/50
115/115 [==============================] - 33s 286ms/step - loss: 0.1142 - accuracy: 0.9584 - val_loss: 0.3169 - val_accuracy: 0.9196
Epoch 45/50
115/115 [==============================] - 33s 290ms/step - loss: 0.0686 - accuracy: 0.9762 - val_loss: 0.3680 - val_accuracy: 0.9040
Epoch 46/50
115/115 [==============================] - 33s 288ms/step - loss: 0.0925 - accuracy: 0.9680 - val_loss: 0.4898 - val_accuracy: 0.8705
Epoch 47/50
115/115 [==============================] - 33s 287ms/step - loss: 0.1727 - accuracy: 0.9410 - val_loss: 1.0415 - val_accuracy: 0.7835
Epoch 48/50
115/115 [==============================] - 33s 287ms/step - loss: 0.1194 - accuracy: 0.9612 - val_loss: 0.3739 - val_accuracy: 0.8929
Epoch 49/50
115/115 [==============================] - 33s 287ms/step - loss: 0.0866 - accuracy: 0.9697 - val_loss: 0.2848 - val_accuracy: 0.9219
Epoch 50/50
115/115 [==============================] - 33s 288ms/step - loss: 0.0884 - accuracy: 0.9694 - val_loss: 0.6826 - val_accuracy: 0.8438
```

Fig.3.5.8: Accuracy and loss for 50 epochs (3)

3.6 Research Analysis:

The classification and improved accuracy of accurately forecasting diseases are the ultimate goals of the proposed endeavor. The suggested model successfully makes the right identification with almost 89.58% accuracy while taking into account various diseases that affect plant leaves. Because I took less images due to the hard disk limitation in Google Colab, the accuracy did not turn out as intended. With CNN deep learning architecture, this is possible. By changing the number of layers, the learning rate parameter, and the optimizer employed, the suggested method's performance is further enhanced. In addition, by utilizing the transfer learning principle, the model's outcomes may be contrasted with the current CNN design.

CHAPTER 4

IMAPCT ON SOCIETY AND ENVIRONMENT

4.1 Impact on Society

Diseases control procedures can be a waste of time and money if the disease and the disease-causing agent are not properly identified. This can lead to additional plant losses. As a result, accurate disease diagnosis is necessary. Symptoms are frequently used by plant pathologists to identify disease problems.

4.2 Impact on Environment

Plant diseases are essential to investigate because they cause plant and product loss. The many sorts of losses occur in the field, in storage, or at any point between sowing and harvesting. Diseases are accountable for both direct and indirect monitory loss. On the other hand if one plant is affected by any diseases in the field other plants can also get affected by that on plant. Also soil of the field can be hampered. So, if this study is appropriately utilized, it can detect the disease sooner and, as a consequence, farmers and plant pathologists can take the required actions to erase the disease's damage.

CHAPTER 5
IMPLEMENTATION AND TESTING

5.1 Summary of the Study

In order to detect five specific plant diseases (Strawberry Leaf scorch, Corn Cercospora, Corn Common Rust, Grape Black Rot, Grape Esca Black Measles, Grape Leaf Blight, Cherry Powdery Mildew, Grape Black Rot, and Grape Esca Black Measles) in corn, bell pepper, grape, and cherry strawberries, I have analyzed the data. I conducted a literature research on this particular field of study and took all the material I needed from the internet.

In order to build a convolutional neural network for the purpose of digital image processing in this article, I used Tensorflow and Keras; I used the Google Colaboratory as a platform. I have identified a particular number of plant diseases from my chosen dataset by using the algorithms.

5.2 Conclusion

There are numerous research projects underway in the areas of agriculture, leaf diseases detection, weed detection by image processing. The difficulties and restrictions associated with employing image processing for leaf disease identification, including as problems with picture quality, illumination, and the requirement for specialist expertise to recognize and categorize illnesses. The potential uses of image processing for identifying leaf diseases, such as in forestry, agriculture, and other fields where plant health is crucial. In this study, I created a CNN model for very accurate leaf disease detection. The model performed quite well in categorizing the various diseases. The automated method might increase the effectiveness and precision of leaf disease diagnosis, allowing for prompt treatment and reducing crop losses. Additional leaf diseases might be included in the model in the future, and its hyper parameters could be adjusted for even better performance. In conclusion, a review of the literature on leaf disease detection using image processing might offer insightful information on the state of the art in this area and point up potential directions for further study.

5.3 Further Implication of the Study

This research is just the start of a protracted journey. I have a goal to make this project deeper and more informational so that it can have greater implications. My dataset will be larger over time, and its visual representation will become clearer and more informative. My next project involves using ReactJs to create an AI-based software that will be simple for both agriculture experts and regular people to use, such as farmers who may not be very familiar with AI. The app will provide details on leaf diseases, the nutrient for which the problems are occurring, and the anticipated remedy. This app will benefit global agriculture in addition to Bangladesh.

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