

**PLANT DISEASE DETECTION USING IMAGE PROCESSING CNN
TECNOLOGY**

BY

**Md. Rakibul Hassan
ID: 171-15-8814**

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

Supervised By

Ms. Nazmun Nessa Moon
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Raja Tariqul Hasan Tusher
Senior Lecturer
Department of CSE
Daffodil International University



DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled “**'Plant' Disease Detection Using Image Processing CNN Tecnology – Grapevine, Strawberry, Apple, Cherry, Corn, Peach**” submitted by Md. Rakibul Hassan, ID: 171-15-8814 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment 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 **9th September 2021**

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Dr. Touhid Bhuiyan

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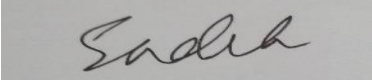
Gazi Zahirul Islam

Assistant Professor

Department of Computer Science and Engineering

Faculty of Science & Information Technology

Daffodil International University



Internal Examiner

Md. Sadekur Rahman

Assistant Professor

Department of Computer Science and Engineering

Faculty of Science & Information Technology

Daffodil International University



External Examiner

Shah Md. Imran

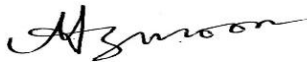
Industry Promotion Expert

LICT Project, ICT Division, Bangladesh

DECLARATION

I hereby declare that, this project has been done by us under the supervision of **Ms. Nazmun Nessa Moon, Assistant Professor, Department of CSE** 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

Supervised by:



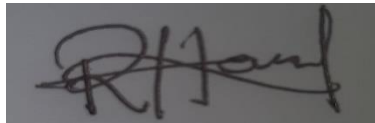
Ms. Nazmun Nessa Moon
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:



Mr. Raja Tariqul Hasan Tusher
Senior Lecturer
Department of CSE
Daffodil International University

Submitted by:



Md. Rakibul Hassan
ID: 171-15-8814
Department of CSE
Daffodil International University

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I would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

Depression My Project 'PLANT DISEASE DETECTION USING CNN TECHNOLOGY' works with disease detection and identification for Grapevine, Strawberry based on image processing. There is very big improvement was been made in the field of image preparing and Artificial Intelligence and its applications are used in many different parts of designing. People have already entered the time of digitalization. We caught pictures with the help of advanced cameras and the more clear picture are produce then better ,useable and productive the result's and outcome. In this report I have done an arrangement of fresh, somewhere infected and fully sick leaves. I have been utilizing the HSI shading model to make group of my properties and furthermore I have utilized Neural Network (CNN) Tools for AI to investigate the outcomes. Although measurements for the plant features are fundamental elements for plant science and research also related applications. The information's are related to plant features that principally useful for the applications used in plant agricultural research and growth modeling also on farm production. Past direct measurement methods are generally simple and not so much reliable, on the other hand they are very much time consuming, cumbersome laborious. The proposed vision on the basis of methods that are efficient in observing and detecting the exterior disease and other features. In this present state, image processing algorithms are developing quickly, to detect plants diseases by recognizing and identifying the particular color frame of the individual affected area. Eventually, the rotted area is subdivide from an image. Then the area of decayed leaf chunk was deduced from the Grapevine and Strawberry plants featured data. In my case, the outcomes have showed an encouraging execution of this automated vision-based system, I have achieved 91% accuracy in practice with complimentary validation.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

By 2040, the worldwide production of harvest should be increased by half at all times to meet the expected demand. Much of the production is currently taking place in Africa and Asia, where 84% of farmers have almost no agricultural capacity. As a result, misfortunes of yield are more remarkable than half; vermin and diseases are fundamental. The usual technique for human examination by visual examination is not at this stage possible when crop diseases are characterized. The progress of PC view models gives a quick, standardized and accurate response to this problem. A classifier can also be transmitted as an application when prepared. Easy to use, everything you need is a web partner and camera equipped cell phone. 'iNaturalist' and 'Plant Snap' mainstream business applications show how they can be done. In addition to conveying mastery to customers and also to building an intuitive web-based social network, both apps have achieved success. Mobile phones continue to be more accessible and reasonable every year. By 2020, the world's cell phone customers were approximately 5 billion. One trillion customers are located in India and one trillion in Africa. These Figurers have increased reliably every year for the last decade, as stated by Statists. As such, it is accepted that AI applications are an important task to mold the eventual destiny of cultivation.

The use of CNNs in the arrangement for plant diseases has achieved excellent results as of late. The multi-faceted administered network has been positive among experts as the prevailing results have steadily increased. CNN structures have changed considerably since the arrival of LeNet (1988). Complex capabilities have become a dominant feature in the present-day design, for example ReLu nonlinearity and pooling. Such advances have helped to reduce time and error preparedness. Above all, the progress of engineering was an essential interest in huge and complex datasets in the 21st century. The pre-preparation of information is essential for the implementation of a model. It is difficult to detect viral, bacterial and contagious diseases, with regular coverage of indication

Manifestations can be any quantum shading, form or capacity contrasts that result from the reactions of the plant to the mycobacteria. Given this diversified nature, the use of RGB information is desirable. This creates clear concussion-free images that can take more to prepare than gray information but are usually more suitable for distinguishing between models of plant disease

More modest data sets or different information can affect the reliability of a model. This can be seriously monitored by using methods such as growth or moving learning. Extending the preparation of images could not only reduce over fitting, but could also improve the general performance of the model. This can be done by adding abilities such as zooming, pivoting or adding changes in shading or differentiation. Nevertheless, the modified photos should mirror the approval data set assumptions. If misapplied, the accuracy of the classifier may deteriorate, even though further information is created. In addition, when working with more modest datasets, the strategy for moving learning has shown very success. The loads of a preprepared model must be adjusted here. For this reason the Image Net database is usually used and contains over 13.5 million images. ResNet (2015) presented additional heavy capacity in its ongoing design. This combines dynamic blanks as well as heavy bunch standardization. This allows for a much higher learning rate to be prepared. Wu et al. in 2019 compared ResNet to VGGNet, Google Net and Dense Net, concluded that ResNet delivered the best results in order to cure diseases of grapevine leaf. In current explorations, custom formats are usually fused into the foundation architecture such as Alex Net, Le Net and Google Net (2014). In light of Le Net, in its analysis of the plants disease order such as grapevine, strawberry suggested such a construct. The model consisted of three convolution layers, a max pooling layer and an MLP with Relu actuation that was fully associated and achieved a precise 99 percent rate.[2]

Mohanty et al. revealed these advantages in a 2016 survey of harvest diseases arrangements. In contrast to a model that worked without preparation there, unrivaled results were recorded using moving learning (Image Net). Because Image Net contains images superfluous to an explicit task of a plant, it is flawed whether it is possible to upgrade everything before preparing everything in the herbal information base. Ebb and Flow.

Research recommends that Image Net pre preparation can sum up better and that explicit work assignment pre-preparation may reduce over fitting in any case. These claims are, however uncertain they may be. The subject is generally neglected due to a lack of huge organic data sets. Growth may also be used for the models in question. Nevertheless the impact is greater when used for unprepared CNNs due to information previously gathered by a particular model. The quality and type of information preparation greatly affects the abilities of the model. The accuracy of a classifier is subject to this creation when prepared for symbolism which contains plain baseline information. In this way, when tried with field photos, it is likely to be untrustworthy. [1]

Segmentation can show success by isolating a leaf from its experience. In addition, this strategy can be used in situations in which the classifier needs scenic attention. For instance, the level of mycobacterial harm around the tissue may be understood instead of merely the polluted tissue. Segmentation is certainly not another idea. Since the 1980s, it has been used by companies that group diseases. In fact, great results were taken into account even at this early stage. Early reviews also helped to distinguish the limitations and showed that the strategy was unable to overcome halftone image quality. Accordingly, focusing on the significance of cautious information assortment and preprocessing. The pertinence of segmentation proceeds into 2021. The type of information used also indicates the stage of disease and location. Explicit symbolism should be used for the recognition of early diseases. Fluorescent chlorophyll (CFI), in-farowed thermography (IRT), hyper spectral symbolism (HSI) and multispectral sbolization (MSI) are explicitly capable of distinguishing manifestations not yet visible to the eye. [1] They can be used alone or attached where appropriate. For the model, IRT recognizes a remarkable temperature expansion. Days before indication, this was effective in diagnosing crop diseases and fruits diseases that remember fleece mound for roses and FHB in wheat. As a result of the restricted accessibility of such information, this topic is moderately neglected. With the development of the scholastic premium in the region, the innovation expected to capture this particular emblem is becoming modest. It is anything but an instrument available to distant ranchers, in any case.

1.2Motivation

In the current era Bangladesh is in fast developing countries and in the early stages, agriculture is the backbone for the nation's progress. The field faces obstacles because of ideas of industrialization and globalization. In addition, awareness and developmental needs should be integrated into the psyches of the younger age. In all areas we still use some old agriculture methods until now, the innovation of a day is indispensable. Reconnaissance of plant disease leads mistakenly to huge losses of return, time, cash and item nature. For an effective development, distinguishing the state of the plant is a major part. In past times, however, the achieved individuals physically identify themselves but the expectations are becoming increasingly intense due to numerous ecological changes. We can thus use imaging methods to prove plant disease recognizably. We can see the disease signs in leaves, stalks, blooms etc. so we use leaves here to identify influenced plant diseases.

1.2Rationale of the Study

In long reports the significance of sentences changes; some are more focal than others. Earlier work has explored strategies to quantify the general significance sentences (KO Et Al., 2002; Murata et al., 2000). In this work we embrace a specific perspective on sentence significance with regards to record characterization. Specifically, we accept that archives include sentences that straightforwardly uphold their arrangement. We call such sentences reasoning's. With regards to record characterization. Specifically, we accept that archives include sentences that straightforwardly uphold their arrangement. We call such sentences reasoning's. The idea of reasoning's was first presented by Zaidan et al. (2007). To outfit these for order, they proposed changing the Support Vector Machine (SVM) target capacity to encode an inclination for boundary esteems that bring about examples containing physically explained reasoning's being more certainly grouped than 'pseudo'- cases from which this reasoning's had been tried. With regards to record characterization. Specifically, we accept that archives include sentences that straightforwardly uphold their arrangement. We call such sentences reasoning's.

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1.3 Rationale of the Study

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1.4 Expected Outcome

Expected outcome of this research- based project:

- ☐ Detect Disease and fresh leafs around 95% accuracy.
- ☐ Learn and train the set to its upmost ability.
- ☐ There will be shown with graph that shown the effected level.
- ☐ here will be output a predicted disease type or healthy plants species.

1.5 Report Layout

In **Chapter 1:** In this section I can look at the introduction, motivation and targets and talk about how the expected result is respected etc. Part 1 in a word is the development of this project.

In **Chapter 2:** I introduced the key state of our work in this section and talked about the company status. I also have the related transactions that have been examined with this territory. Their findings and restrictions are summarized and therefore the extension and difficulties of the exam are also mentioned.

In **Chapter 3:** In this section I discussed research topic and instrumentation discussions, information spectrum strategy, factual investigation, and implementation requirements.

In **Chapter 4:** Results of the trial and discussion Experimental and descriptive results are presented.

In **Chapter 5:** The exhibition of the whole company was shown in this part. Presents an overview of references and an overview.

In **Chapter 6:** I made the last judgments in this last section concerning the epilog of the entire task.

CHAPTER 2

BACKGROUND

2.1 Introduction

Technology makes our lives so fast and easy wherever we want to touch everything. We will discuss in this chapter related research or project on Deep Learning related to data classification. The entire strategy of creating the model for recognition of plants using deep CNN is further described. The entire process is divided into a few vital phases in the following sub-sections, beginning with photos of social affairs for classification using deep neural networks. We will discuss previous related work in the first section, then show the results or a summary of my study of the related work in the second section of this section, and then discuss about the advantages and challenges facing the project.

2.2 Related Works

Kim (2014) proposed the basic CNN model we present in this work and then expand it. The properties of this model have been precisely investigated (Zhang and Wallace, 2015). We also note that Zhang et al. (2016) extended this model to include several pre-prepared word embedding arrangements. Generally concurrent with Kim, Johnson and Zhang (2014) proposed a comparative engineering for CNN, despite their trading of (pre-prepared) word embedding in one hot vectors. A Survey of Best Practices. It introduced an outline of best practices in the examination of (differential) co-articulation, co-expression networks, differential systems administration, and differential availability that can be found in microarrays and RNA-seq information, and shed some light on the investigation of scRNA-seq information also. XiaoyanGuo, MingZhang, Yongqiang Dai proposed Image of gasp disease segmentation model dependent on heartbeat coupled neural Network with mix frog jump calculation. An epic picture segmentation model SFLA-PCNN for plant diseases dependent on half and half frogbouncing calculation is proposed. Utilizing the weighted amount of cross entropy and picture segmentation

Minimization as the wellness capacity of SFLA, the picture of potato late scourge disease is taken as a preliminary segmentation picture to locate the ideal setup boundaries of PCNN neural. Picture segmentation is a critical advance in element extraction and disease acknowledgment of plant diseases pictures. Chit Su Hlaing, SaiMaung MaungZaw proposed Plant Diseases Recognition for Smart Farming Using Modelbased Statistical Features. It has demonstrated the benefits of GP circulation model for SIFT descriptor and effectively applied in plant disease characterization. Besides, it proposed highlight accomplishes a decent tradeoff among execution and grouping accuracy. Despite the fact that it proposed highlight can effectively show the SIFT include and applied in plant diseases acknowledgment, it need to attempt to improve our proposed highlight by considering and participation with other picture preparing techniques. [4]

2.3 Comparative Analysis and Summary

Plants are regarded as a source of energy to mankind. Plant diseases can influence the agriculture that can lead to colossal harvest misfortune. As a result, the identification of leaf diseases takes on an essential role in farming. It requires enormous work, time and comprehensive information and skills on plants, however. AI is then involved in the discovery of diseases in plant leaves as the information is dissected in various territories into one of the defined classes. AI is also involved in discovery. Significant news for plant-leaves plant arrangements and different types of plant disease and different characterization techniques in AI are considered as highlights and properties as tone, strength, and measurement. This study aims to evaluate the use of the pre-prepared ResNet34 model for the preparation of a classification of plant disease. The focus will be on three plant species. The products include strawberry, grapevine. The model is prepared for each species to perceive a select number of diseases or strength conditions.

The particular objectives of this exploration are to:

- I. Determine the overall viability of the model in the characterization of diseases that use both the approval and test data.
- II. Compare the model's accuracy when tried with different picture sizes and enlargement settings.
- II. Use the prepared model to make a web application easy to use.

When the model arrives at an accuracy and F1score of more than 80%, it will be acknowledged. In light of the requirements of smallholder ranchers, this examination will be completed. Both cell phone and web associations will have to be installed in the classifier and web application which, as mentioned recently, continue to reach remote areas. The model will be proven with a variety of image sizes and growth settings by recognizing the constraints of essential camera telephones. We have remained careful about awful precision and yield. We have a large range of precision to find the best correlation with the use of measurements.

2.5 Scope of Problem

We wanted to plan the module so an individual with no information about programming can likewise have the option to utilize and get the data about the plants disease. It proposed framework to anticipating leaf diseases. It clarifies about the trial examination of our technique. Diverse number of pictures is gathered for every disease that was arranged into information base pictures and info pictures. The essential credits of the picture depend on the shape and surface arranged highlights.

2.6 Challenges

1) Data Collection

More modest information sets can influence the unwavering quality of a model. This can be monitored seriously, for example by using methods for expanding or moving learning. Increasing image preparation can decrease over fit and improve overall performance of a model. The quality and type of information preparation greatly impacts the abilities of the model. A significant number of accessible datasets, including the customized dataset [3], have also added a large number of photos

For greater precision. Try not to be symbolic of infield. The requirement is intensively examined for such a dataset.

Model Selection

As a result of its importance, model determination is one of the toughest aspects of an exploration project. Data set and Model selection are critical to the success of any investigation. Assuming that we are successful in selecting the model, we should see positive results within the next few months. Choosing a bad one, on the other hand, can lead to disappointment. On the basis of our test data, we have tried a number of different models to determine which is best suited to our exploration project. The Nave Byes Classifier calculation was found to be the easiest and best for us. The classifier work became simpler when we discovered that it has a simple to use library. As a result, we created this model for our project.

2) Image Pre-processing and Labeling

Data labeling is additionally a most significant part for makes code so quicker. It was the main piece of our work. Since it makes code quicker to run and less tedious for information preparing. We use Label Encoder in Python for naming our information. Pictures downloaded from the Internet were in different arrangements alongside various goals and quality. To improve highlight extraction, last pictures planned to be utilized as dataset for profound neural organization classifier were preprocessed to pick up consistency. Moreover, method of picture preprocessing included trimming of the relative multitude of pictures physically, making the square around the leaves, to feature the district of interest (plant leaves). During the period of gathering the pictures for the dataset, pictures with more modest goal and measurement under 500px were not considered as substantial pictures for the dataset. In that manner, it was guaranteed that pictures contain all the required data for highlight learning. Pictures utilized for the dataset were picture resized to lessen the hour of preparing, which was consequently processed by composed content in Python, utilizing the Open-CV system. Numerous assets can be found via looking across the Internet, however their pertinence is frequently temperamental.

In light of a legitimate concern for affirming the accuracy of classes in the dataset, at first gathered by a watchwords search, agricultural specialists analyzed leaf pictures and marked all the pictures with suitable disease abbreviation. In this stage, copied pictures that were left after the underlying emphasis of social occasion and gathering pictures into classes depicted in Section 4.2 were eliminated from the dataset, the input data of this project Figure 2.5.1, Figure 2.5.2 [1] and Figure 2.5.1.

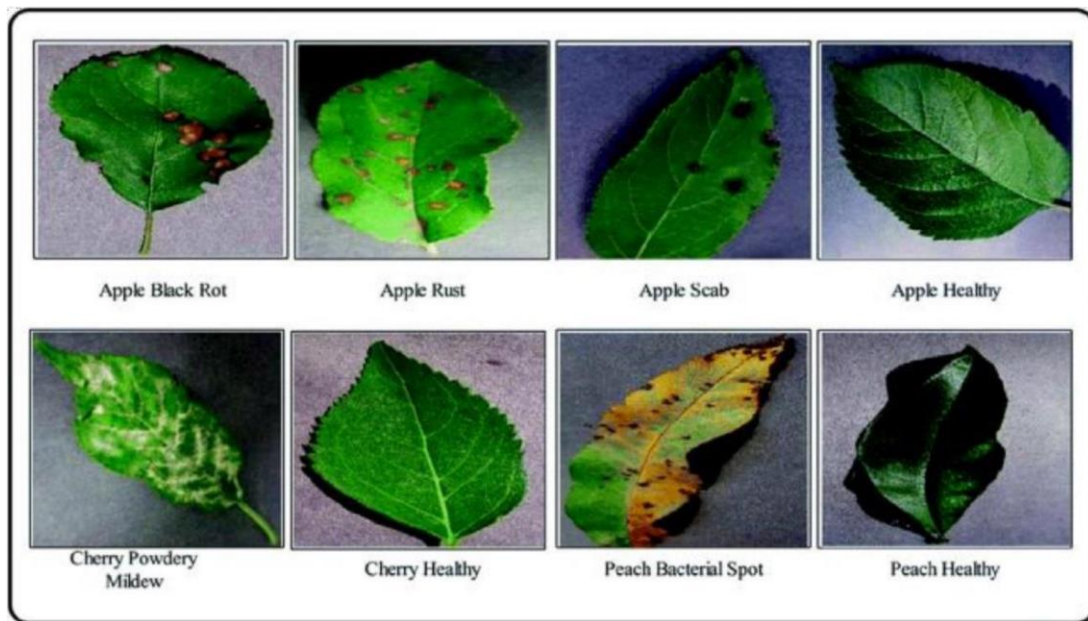


Figure 2.5.1: Pre-Processed Input Phase One - padding mode



Figure 2.5.2: Pre-Processed Input Phase Two- brightness changes



Figure 2.5.3: Pre-Processed Input Phase Two Example Images

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

Identify, measure, and investigate data using research methodology of my examination technique will be examined and described in this section. There will also be a discussion of the research project's apparatuses, information collection, the research subject, pre-handling and preparation, factual examination, and its execution.

3.2 CNN_Plan of Attack

CNNs are certainly not a simple accomplishment to dominate. This is the initial phase in your excursion - so get it together on the rudiments prior to beginning. A Convolutional Neural Networks Introduction as it were-

Step 1: Convolution Operation

The principal building block in our arrangement of assault is convolution activity. In this progression, we will address include indicators, which essentially fill in as the neural organization's channels. We will likewise examine highlight maps, learning the boundaries of such guides, how examples are recognized, the layers of identification, and how the discoveries are outlined shown in Figure 3.2 [5]

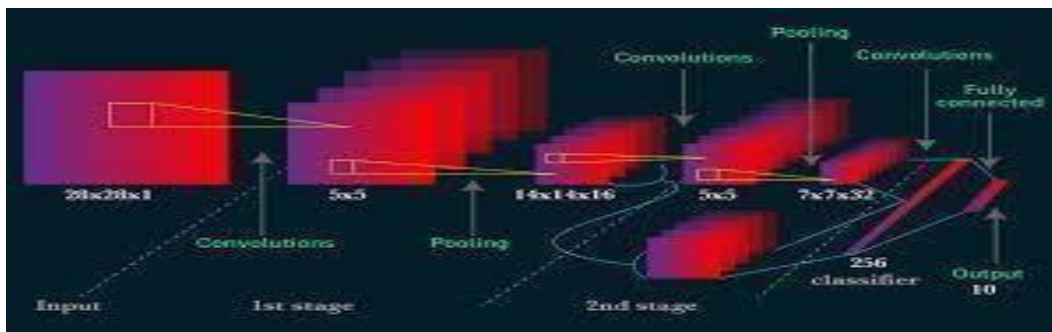


Figure 3.2: Image Classification steps with CNN

Step 2: RELU LAYER

The second piece of this progression will include the Rectified Linear Unit or ReLU. We will cover ReLU layers and investigate how linearity capacities with regards to Convolutional Neural Networks. However, a brisk exercise to improve your aptitudes isn't inherently harmful.

Step 3: POOLING LAYER

Pooling is the subject of this section, and we'll see how it works in general terms. However, we're going to focus on a specific form of pooling: maximum pooling. Different methods of calculating the mean (or total) will be discussed. After this, we'll see a visual intelligent device that will Figure out the whole concept for us

Stage 4: FLATTENING

When working with Convolutional Neural Networks, the straightening cycle and how we go from pooled to leveled layers will be briefly discussed.

Stage 5: FULL-CONNECTION

In this section, we'll summarize everything we've talked about so far. With the knowledge of this, you'll have a clearer picture of what Convolutional Neural Networks do and how the "neurons" that are created eventually become familiar with the arrangement of images.

After a while, we'll come to an end and give a quick recap of the idea explored in the episode. It's worth taking a look at the additional training exercise that covers Softmax and Cross Entropy if you think it'll be beneficial to you. Even though it's not required, you'll likely run into these concepts when working with Convolutional Neural Networks, and it'll be a huge help to be familiar with them. Extra information on SoftMax and Cross-Entropy to help you understand Convolutional Neural Networks. Let's get started

3.3 Research Subject and Instrumentation

Information is the primary piece of the exploration project. It is an exceptionally basic part for a specialist to discover wonderful information and amazing calculation or model for our examination work. We likewise needs to learn about related examination papers. At that point we need to settle on a few choices:

1. Which information should be gathered.
2. That gathered information are alright.
3. How every information should be coordinated.
4. How every information should be labeled.

3.4 Data Collection Procedure

There are thousands of images of grape, corn, strawberry, apple, cherry, peach etc. that I've collected and compiled into a single data bundle. An unvarying model's quality can be impacted by smaller datasets or unvarying data sources. There are a few ways to do this, such as using procedures such as expansion or move learning. A model's overall performance can be improved by increasing the number of pictures taken. Qualitative data preparation has a significant impact on a model's performance. When a classifier's accuracy is based on symbolism that contains basic foundational information, it becomes dependent on this structure. When it comes to in-field photography, it's likely to be temperamental as a result. There are a large number of plant disease datasets that are publicly available. [3], and furthermore added an enormous number of pictures information for better accuracy. The requirement for such a dataset is featured intensely in examination.

All phases of article acknowledgment research require fitting datasets, from the preparation stage to the evaluation of acknowledgment calculations. Thirteen classes focused on plant diseases that could be determined from the outside by looking at leaves.

One more class was added to the dataset to distinguish healthy leaves from diseased ones. It contains just pictures of solid leaves. An additional class in the dataset with foundation pictures was advantageous to get more precise order. [3].

All copied images from various sources were removed at this stage by using the looking at method in created python content. To find out if there were any duplicates in a picture's metadata (name, size, and date) As a result of the computerized expulsion, the images were carefully examined by human specialist.

The next step was to improve the study and prepare the organization to become familiar with the features that distinguish one class from the others, which was the next stage. In this way, the organization's ability to become familiar with the appropriate details has been increased by using larger images. Finally, a database containing around 52000 pictures for preparing and 28000 pictures for approval has been created and is available for use. To illustrate the growth cycle, refer to Section 4.2

1) Data Pre-processing

Data and Information pre-preparing is a handling that way to the pre period of handling datasets. By and large crude information pictures can't perform tasks and produce anticipated result. Subsequently, information pre-handling is required. Additionally it is viewed as perhaps the main pieces of exploration. In this stage, we have gathered in excess of 52000 pictures.

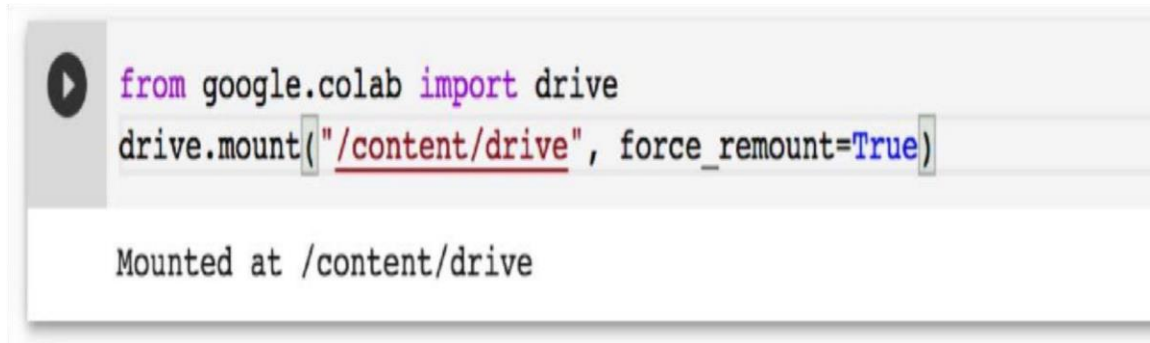
Here, to foresee the diseases. We provided a sample input preprocessed image on Figure 2.5.1.

2) Data Organizing

Data Images Information getting sorted out is an arrangement of put together information. In this way, for getting sorted out information, we have tried and prepared the information and saved them in two envelopes. We have additionally utilized approval organizer to check train information approval in information arranging. At that point we have made sub-organizers in the test and train envelopes like online media influence, gaming influence, sway on social relationship, and sway on scholastic outcome and so on.

3)Import Image Data

At this portion we have some code in Co-Lab that import our data from google drive. And all image data we have to upload early in google drive. We use here import with Python in Google Co-Lab. Some process is given below Figure 3.4.1.



```
from google.colab import drive
drive.mount("/content/drive", force_remount=True)
```

Mounted at /content/drive

Figure 3.4.1: Data importing by Colab python3.8

After importing image data directory, image preprocessing and labeling in Figure 3.4.2-



```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

# We have stored data in My drive/agan folder
DATA_PATH = '/content/drive/My Drive/real New Plant Diseases Dataset(Augmented)'

# Our test and train directory have specified below
train_data_dir = '/content/drive/My Drive/real New Plant Diseases Dataset(Augmented)/train'
validation_data_dir = '/content/drive/My Drive/real New Plant Diseases Dataset(Augmented)/test'

# Configuring the dataset
# Batch size is 10 (Will take 10 image for each run)
batch_size = 10
# Epoch is 50 (Will run 50 times)
epochs = 10
# Image height and width reduced here for faster train and test
img_height = 150
img_width = 150
```

Figure 3.4.2: Resize and format of image data

4) Data Processing Layer

In fact, profound learning CNN models to prepare and test, each information picture will go it through a progression of convolution layers with channels (Kernels), Pooling, completely associated layers (FC) and apply Softmax capacity to order an article with probabilistic qualities somewhere in the range of 0 and 1. The beneath figure is a finished progression of CNN to handle an information picture and groups the articles dependent on qualities. The steps are in Figure: 3.3.

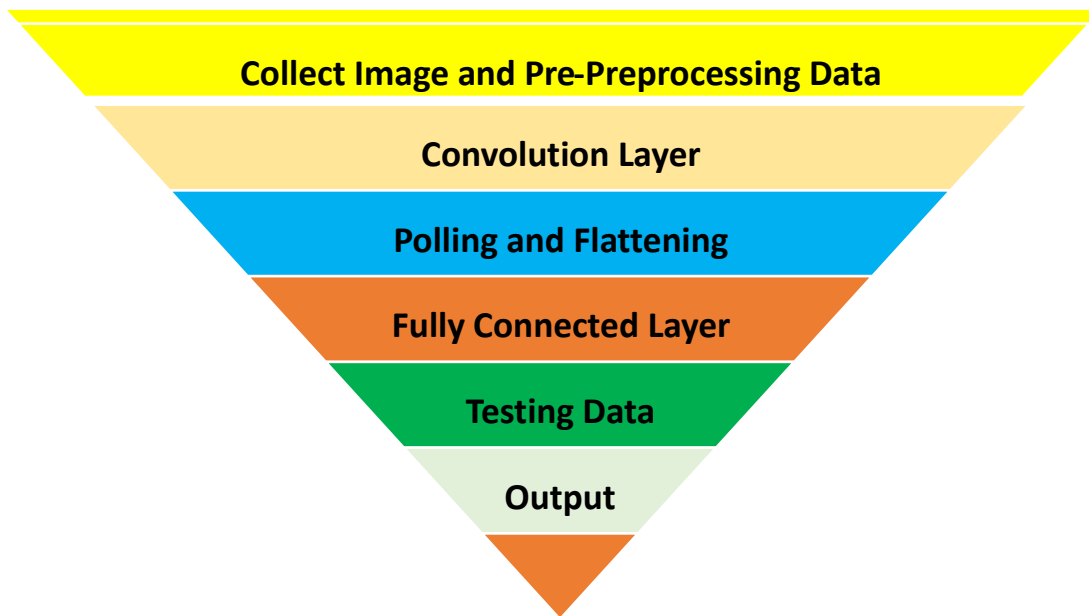


Figure 3.4.3: Image Classification steps and data processing

3.5 Statistical Analysis

The amount of our total data is more than 14000 that we collect but after preprocessing we get total 13000 image data. The accurate image data amounts are given below in Table 3.1.

Species	Class	No. of Images
Strawberry	Healthy	1223
Strawberry	Leaf scorch	1300
Peach	Healthy	3000
Peach	Bacterial spot	2444
Grape	Healthy	1889
Grape	Leaf blight	1998
Grape	Black measles	1788
Grape	Black rot	1377
Corn	Healthy	2999
Corn	Northern leaf blight	2308
Corn	Common rust	3000
Corn	Gray leaf spot	1986
Cherry	Healthy	3200
Cherry	Powdery mildew	2800
Apple	Healthy	1800
Apple	Cedar apple rust	1300
Apple	Black root	2024
Apple	Apple scab	2245

TABLE 3.1: CLASSIFICATION OF THE DATASETS

3.6 IMPLIMENTATION REQUIREMENTS

• Python 3.8

Python 3.8 is a Python version. It is an advanced programming language. The greater part of the analysts use it to do their examination. It is an enthusiastically suggested programming language for AI based work and it is well known among new age's software engineers since it is exceptionally simple to learn and comprehend.

- **Google CoLab**

Google CoLab is an allowed to utilize open source merchant of Python programming language. We can work here online through our program just as through Jupiter note pad. Be that as it may, the primary advantage of Google CoLab is it gives us free online virtual GPU access.

- **Hardware/Software Requirements**

1. Operating System (Windows 7 or above)
2. Web Browser (Preferably chrome)
3. Hard Disk (Minimum 4 GB)
4. Ram (More than 4 GB)
5. Intel(R) Core™ i5-9300H CPU @ 2.40GHz
6. Graphics NVIDIA GeForce RTX 2060 6GB GDDR6

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSION

4.1 Experimental Setup

In This segment portrays the means engaged with making and sending the classifier. Order by CNN is partitioned into three stages which tackle separate assignments. All work engaged with this exploration was finished on one machine, with particulars recorded in Hardware & Software are Memory 8.0GB Processor Intel(R) Core™ i5-9300H CPU @ 2.40GHz Graphics NVIDIA GeForce RTX 2060 6GB GDDR6 Operating system Windows 10 Home 64.

4.2. Information Acquisition

All Plants image symbolisms get from Dataset by Samir Bhattarai, python developer at honest forwarder technology, an open-access store which contains altogether 54,323 pictures. All plants image symbolism begins from the "real New augmented plant disease Dataset" Kaggle dataset. [3] For every species, a select number of classes are picked, with subtleties distinguishable in Table 4.2. To get to this, a test dataset containing 50 pictures, sourced from Google is too set up. These pictures contain extra plant life structures, infield foundation information and fluctuating phases of disease.

Table 4.2: FINAL DATASET USED FOR CLACIFICATION

Species	Class	No. of Images
Strawberry	Healthy	1223
Strawberry	Leaf scorch	1300
Peach	Healthy	3000
Peach	Bacterial spot	2444
Grape	Healthy	1889
Grape	Leaf blight	1998
Grape	Black measles	1788
Grape	Black rot	1377
Corn	Healthy	2999
Corn	Northern leaf blight	2308
Corn	Common rust	3000
Corn	Gray leaf spot	1986
Cherry	Healthy	3200
Cherry	Powdery mildew	2800
Apple	Healthy	1800
Apple	Cedar apple rust	1300
Apple	Black root	2024
Apple	Apple scab	2245

Table 4.2: FINAL DATASET USED FOR CLACIFICATION

4.3. Information Pre-Processing

The dataset is separated into 80% for preparing and 20% for approval. To begin with, increase settings are applied to the preparing information. These are created 'on the fly', with each activity conveying a weighted likelihood of showing up in every age [5] and zoom with crop (scale = (1.0, 1.5)). 'Zoom with crop'.

The settings applied incorporate flipping (arbitrary), cushioning mode was later overlooked subsequent to finding that it had improperly trimmed zones of contaminated leaf. At last, all pictures are resized and standardized. Resizing is completed utilizing a pack work, to 256 x 256. As a pre-prepared model is utilized, the RGB Image Net measurements are utilized to standardize. An example of the last pre-handled pictures is perceptible in Figure.2.5.1

4.4. Arrangement by CNN

1) Phase One – Trialing of Image size: Stage one intends to explore the impact that picture size has on model execution. Altogether, five pictures estimated are tried going from 1280 x 720 to 256 x 256. To start, the Resnet34 pre-prepared loads are downloaded. As a default of move learning, all layers with the besides of the last two layers are frozen

2) Phase two - These contain new loads and are explicit to the plant disease order task. Freezing permits these layers to be disease independently prepared, without back propagating the angles. In precisely thusly.

The 1cycle strategy is utilized to prepare the last layers. With this total, the leftover layers are delivered. To help the adjusting cycle, a plot showing learning rate versus misfortune is created and broke down. From this, a reasonable learning is chosen, and the model is run. With results recorded, the model is re-made to the extra four picture sizes Figure.2.5.1. All means stay predictable in every preliminary including the learning rate. And the convolutional Operation processing in the Figure.4.4. [5]

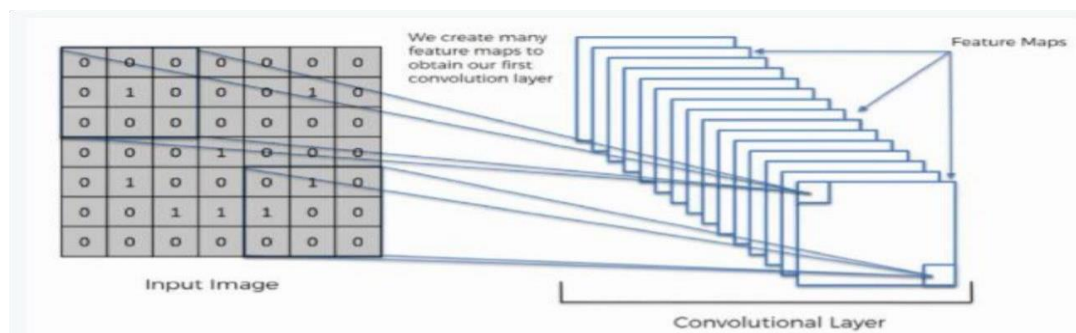


Figure 4.4: Input image process by convolutional layer

3) Phase Two – Model Optimization

Utilizing the most appropriate picture size, the ResNet34 model is enhanced. To additionally improve the model's presentation, extra growth settings are added (Figure. 4.5.2). Activities incorporate splendor changes (0.4, 0.7) and twist (0.5). Next, the last two layers are disengaged and prepared at the default learning rate. With this total, tweaking is performed, running numerous preliminaries to test a progression of learning rates and number of ages.

4.5 The Convolutional Operation:

Here are the three components that go into the convolution activity:

- Input image
- Feature detector
- Feature map

As should be obvious, the info picture is a similar smiley face picture that we had in the past instructional exercise. Once more, in the event that you investigate the example of the 1's and 0's, you will have the option to make out the smiley face in there.

Once in a while a 5x5 or a 7x7 lattice is utilized as an element finder, however the more ordinary one, and that is the one that we will be working with, is a 3x3 grid. The component identifier is regularly alluded to as a "piece" or a "channel," which you may appear to be you dive into other material on the point. It is smarter to recall the two terms to save yourself the disarray. They all allude to something very similar and are utilized conversely, remembering for this course. The convolutional operation shown in Figure 4.5.1. [6]

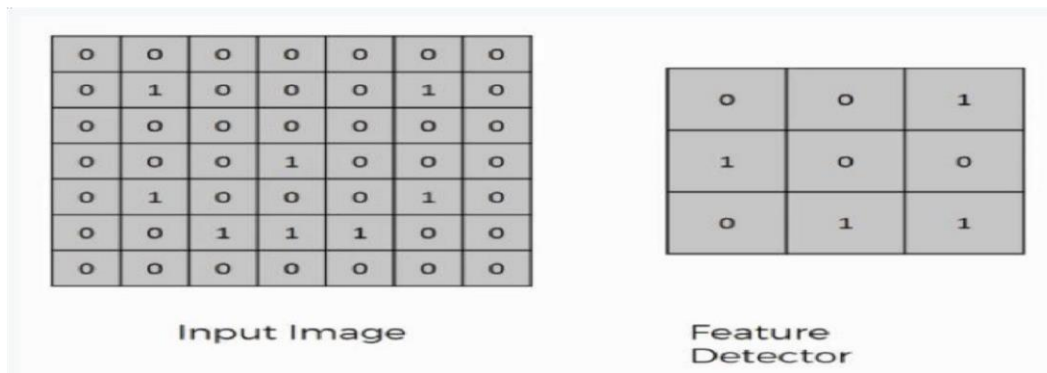


Figure 4.5.1: Convolutional Operation

We can consider the component indicator a window comprising of 9 (3x3) cells. It's significant not to confound the component map with the other two components. The cells of the component guide can contain any digit, not exclusively 1's and 0's. In the wake of going over each pixel in the information picture in the model above, we would wind up with these outcomes at Figure 4.5.2. [5]. We place it over the info picture starting from the upper left corner inside the lines we see separated above, and afterward you include the quantity of cells in which the element locator coordinates the information picture. The quantity of coordinating cells is then embedded in the upper left cell of the element map. We at that point move the element finder one cell to one side and do something very similar. This development is known and since we are moving the element indicator one cell at time that would be known as a step of one pixel. After you have experienced the entire first line, you would then be able to move it over to the following column and experience a similar cycle.

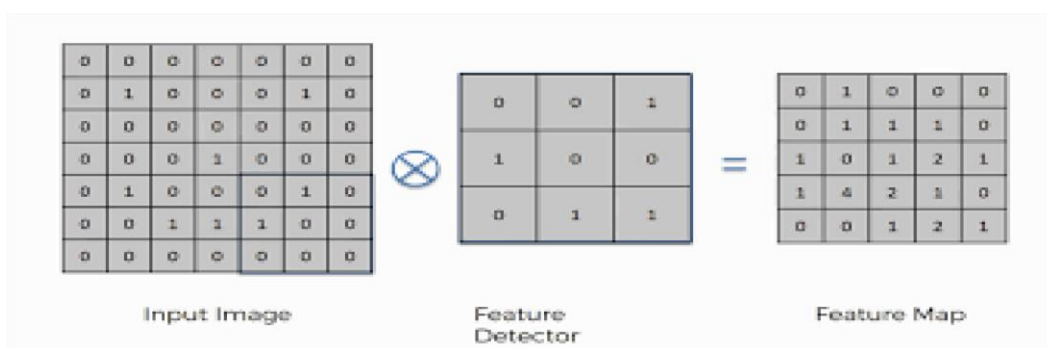


Figure 4.5.2: Convolutional Operation

Incidentally, much the same as highlight locator can likewise be alluded to as a bit or a channel, an element map is otherwise called an initiation map and the two terms are additionally exchangeable

4.6 Full Connection

Here's the place where artificial neural networks and convolutional neural networks crash as we add the previous to our last mentioned. It is here that the way toward making a convolutional neural organization starts to take a more unpredictable and modern turn. How convolutional full connection work shown in Figure.4.6. [5] As we see from the picture beneath, we have three layers in the full association step:

- Input layer
- Fully-connected layer
- Output layer

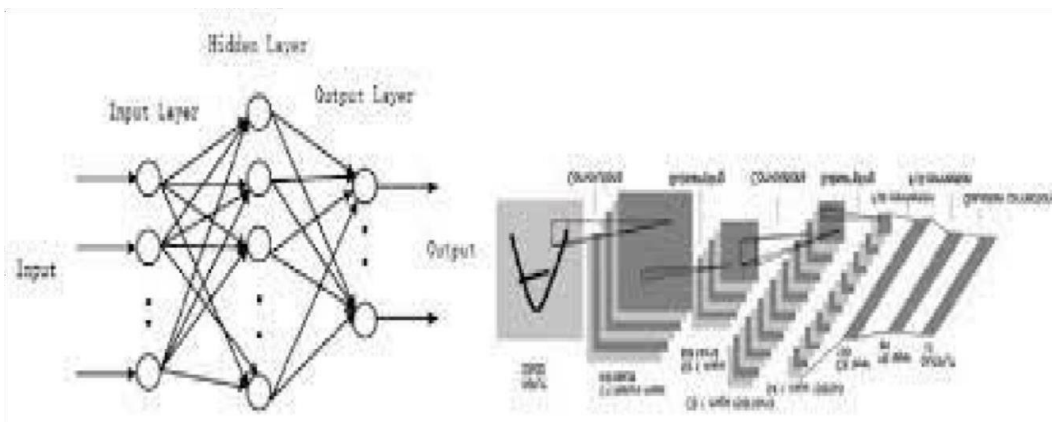


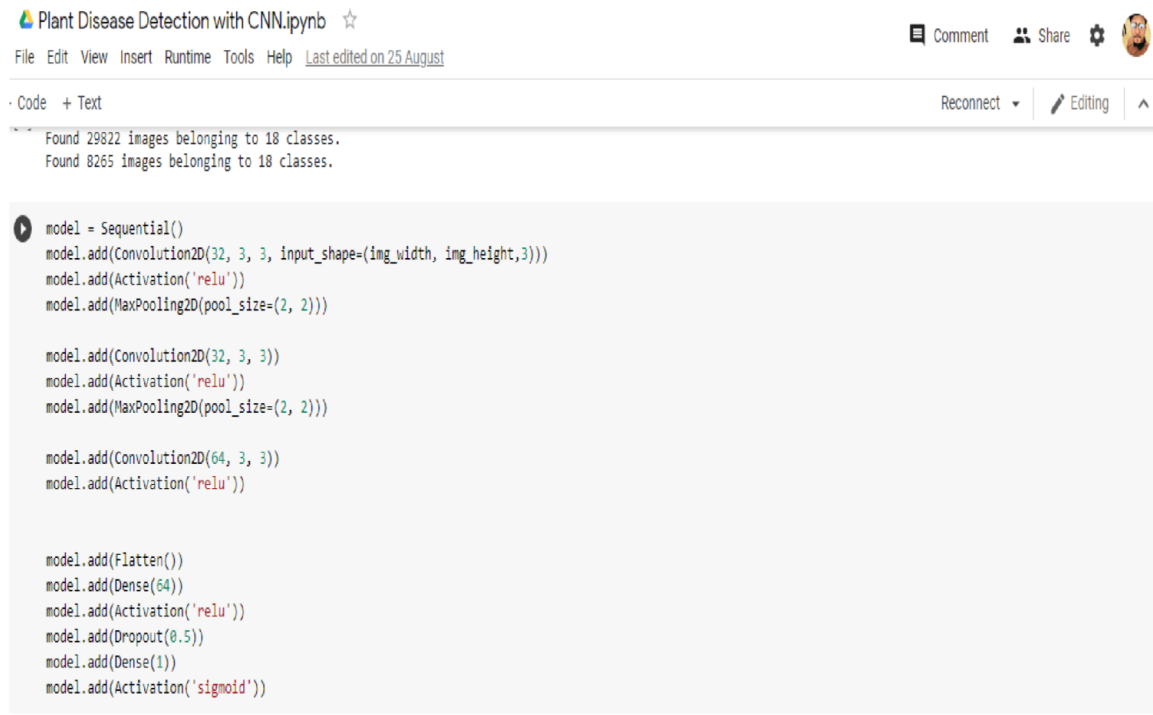
Figure 4.6: Full Connection for the Convolutional

4.7 Experimental Results & Analysis

We have run our dataset to create a model from the given data. It provided us with the desired the output. Then, we have compared academic result with the time and pass column which gave us 95% accuracy. Then again, comparison between health hazard vs time have resulted average in 90% accuracy. Besides, a compare of age with time and pass column was 93% accurate.

4.8 Effect of result -Phase Two

We find the expected output by the code as appeared in Figure.4.8.1. The model predicts any of the classes from the class referenced previously.



```
Found 29822 images belonging to 18 classes.
Found 8265 images belonging to 18 classes.

model = Sequential()
model.add(Convolution2D(32, 3, 3, input_shape=(img_width, img_height, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Convolution2D(32, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Convolution2D(64, 3, 3))
model.add(Activation('relu'))

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1))
model.add(Activation('sigmoid'))
```

Figure 4.8.1: Code for the Convolutional model

Model Here the test output that we have given is plants leaf with leaf spot Phase Two Model Optimization accomplished an accuracy of 0.9365 and F1 score of 0.9359.

- 1) Learning rate v misfortune Used to manage the tweaking cycle. As the learning rate increments past $1e-04$, an emotional expansion in misfortune is capable.
- 2) Fine-tuning the model, learning rate range = $1e-05$, $1e, 04$, ages = 4, Signs of under fitting evident.
- 3) The last advanced model, learning rate range = $1e-05$, $1e, 04$, ages = 10. Preceding tweaking, the model accomplished an accuracy of 0.9465 and F1 score of 0.9359.

Analysis on Figure 4.8.2

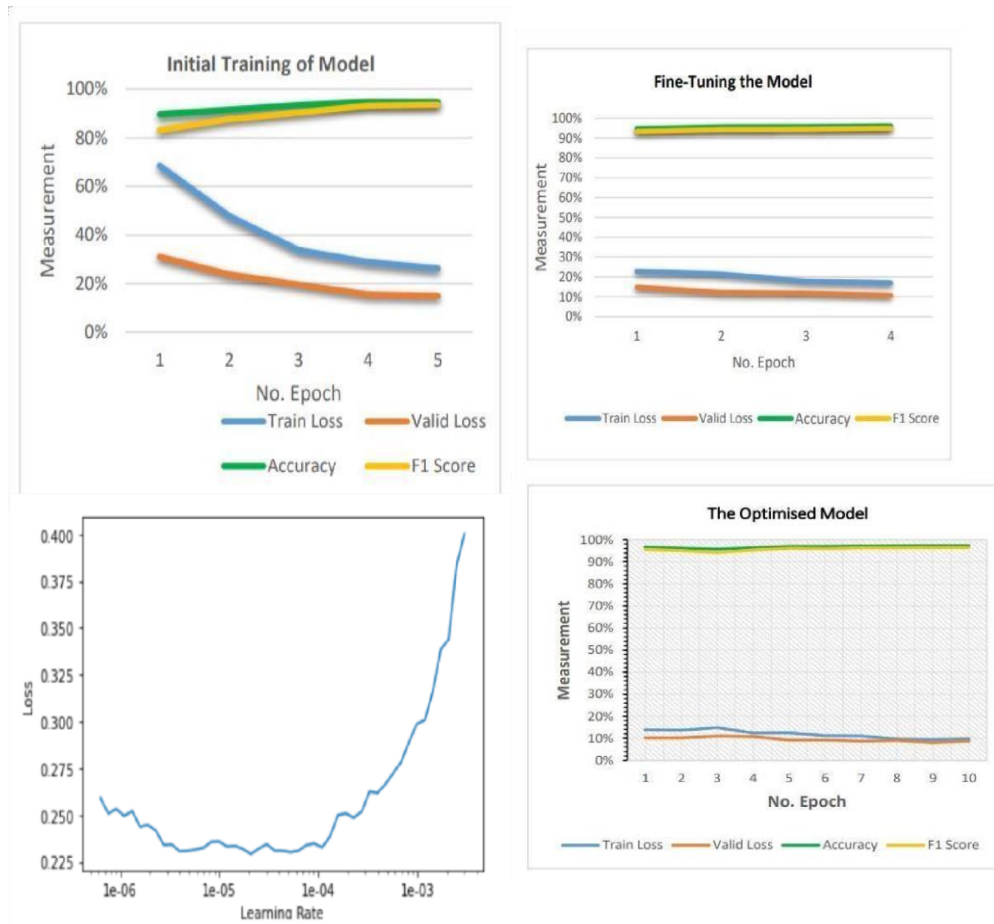


Figure 4.8.2: Model Optimization Analysis

(Figure.4.8.2-1) to help adjusting, a plot portraying learning rate (logarithmic) misfortune was examined (Figure.4.8.2). This shows a generally low misfortune between learning rates $1e-06$ to $1e-04$. As the learning rate increments past $1e-04$ be that as it may, an emotional expansion in misfortune is capable. These realities considered, a few path testing learning rate were completed. A learning rate scope of $1e-05$ to $1e-04$ delivered the best outcomes. By tweaking this hyper parameter, a slight expansion in accuracy (1.5%) and F1-Score (1.3%) was cultivated. On the last age in any case, the end preparing and approval esteems demonstrate that the model might be marginally under fitting (Figure.4.8.23) .To address this, the quantity of ages was expanded efficiently. At Approximately the tenth age, there was a clear

improvement to the attack of the mode. A last perusing introduced a general improvement of 2.8% in accuracy and 3.1 % in F1-score (Figure.4.8.2-4). As expressed before, the approval dataset comprises of an unmistakable creation; one leaf and a plain foundation. For a precise perusing, much the same as those expressed in this part, utilization of the classifier should imitate this picture design. Now we provide the result table in bellow Table 4.8.

Table 4.8:

Test	Image size	Train Loss	Valid Loss	Accuracy	F1 Score
1	153	0.1250	0.1044	0.9004	0.9248
2	175	0.1464	0.1345	0.8925	0.9180
3	212	0.1878	0.1000	0.8924	0.9024
4	243	0.1685	0.1002	0.9062	0.9106
5	255	0.1453	0.1069	0.9033	0.9233

Table 4.8: Result Phase-1(5 epochs)

4.9 Phase Three– Visualizations

Figure 4.9.1 envisions the concealed layer output [7] for each layer, where an info picture of tomato early scourge and its created moderate yields are summed up. In our prepared model, a portion of the moderate yields in the shallow layers feature the yellow and earthy colored sores that are obvious inside the picture (insets with red boundary).

Nonetheless, in the more profound layer (Mixed8), inferable from the convolution and pooling (i.e., down sample) layers, the picture size is too little to even consider interpreting whether such separated highlights have been held. Also, the worldwide normal pooling layer changes pictures over to an element vector that disposes of the spatial data, making it profoundly hard to see how the highlights are taken care of in continuing layers.

It is hard to recognize whether the removed highlights decidedly add to the characterization of the information picture to the right disease class or are utilized for motivation to deny different prospects (e.g., a fuzzy tail raises a chance of a picture containing a feline or a canine however positively not a vehicle). Thus, understanding what the CNN has realized by just investigating the middle of the road yield is deficient.

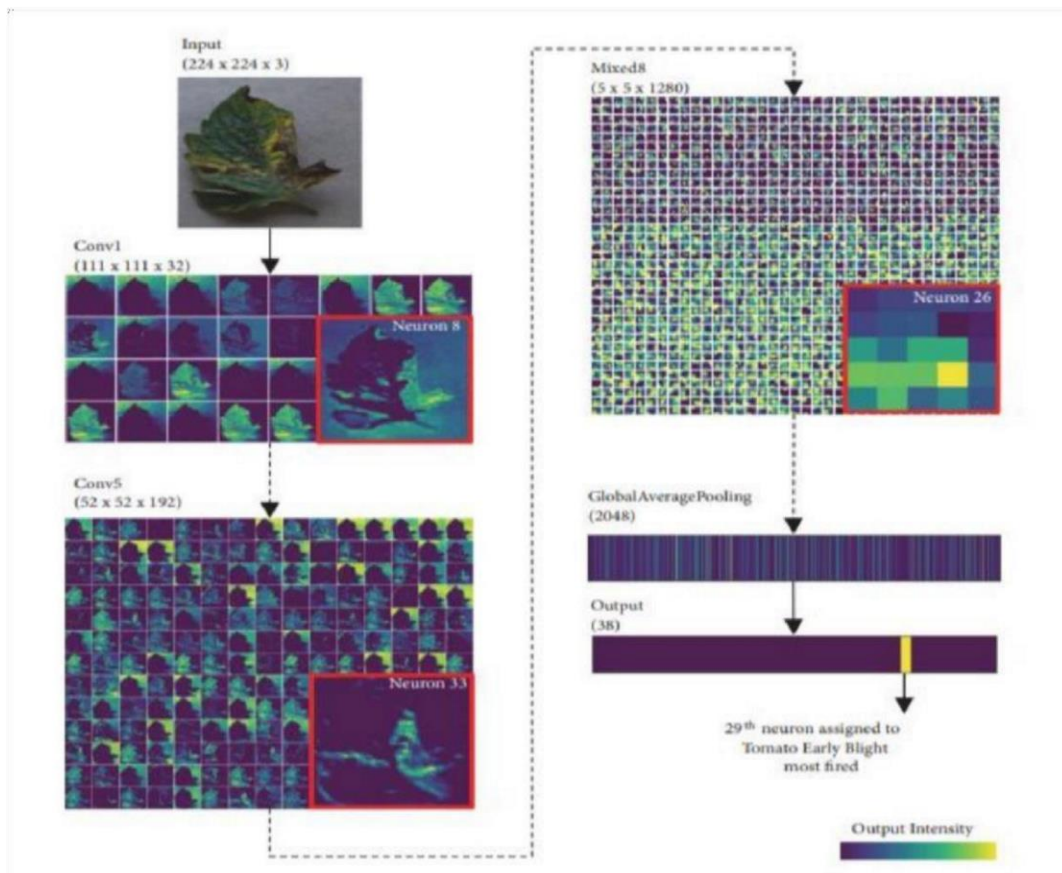


Figure 4.9.1: Plant Disease Visualization output.

Figure 4.9.2 shows the perception for the profoundly contributed neurons (Neuron list: 1340, 1983, 1656, 1933, 1430, and 1856) in the worldwide normal pooling (GAP) layer and their commitment scores created by semantic word reference for 200 pictures of a plants disease (see Materials and Methods for subtleties of commitment score count). [7]

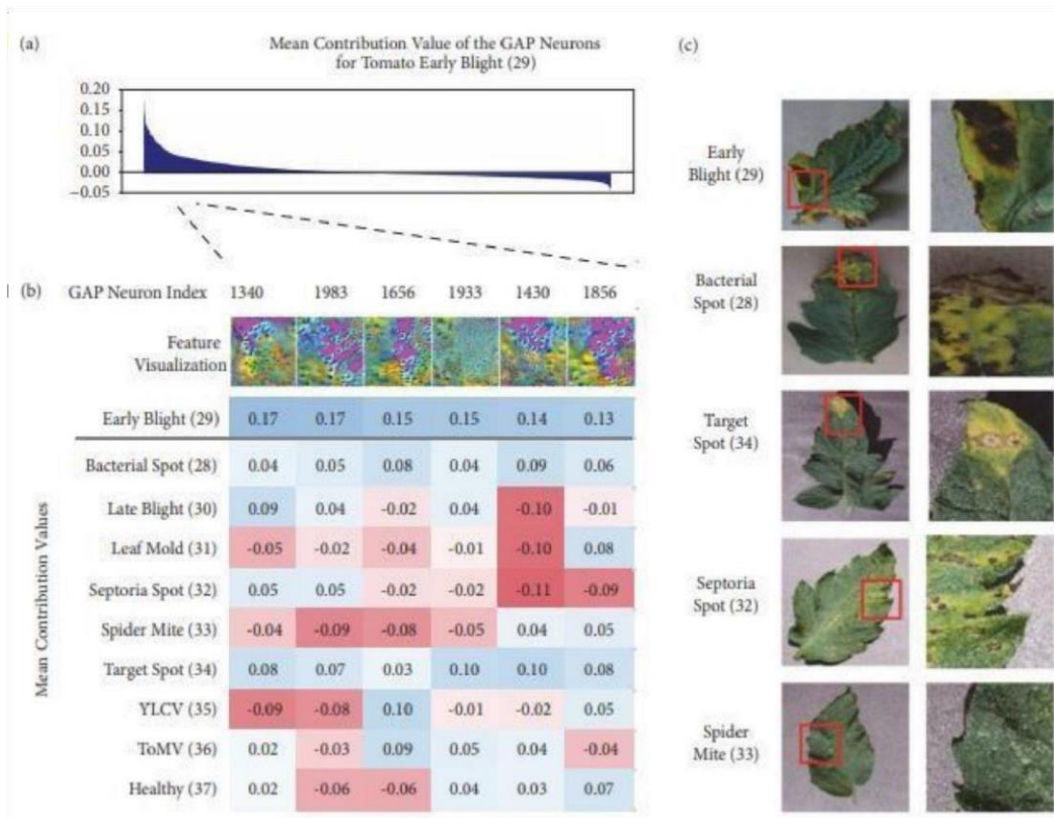


Figure 4.9.2: Plant Disease Visualization of Semantic Dictionary

We additionally show the commitment scores for different diseases of the tomato plant (figure 4.9.2(b)). Highlight perception of the best six contributing neurons for early scourge (mark 29) showed a combination of yellow, green with halfway earthy colored region with a smooth purple, and blue surface (figure 4.9.2(b), include representation). The previous are the average side effects of early scourge; dull hued injuries are went with fringe yellowing (figure 4.9.2(c), red inset), inferring that such highlights are significant for conclusion. The last surface mirrors the constituents of the foundation tone. These neurons decidedly add to bacterial spots to a limited degree (mark 28) and target spots (name 34) that show a comparative aggregate to disease. 4.9.2(a) and 4.9.2(b). Be that as it may, they barely or adversely add to sectorial spots (mark 32) and arachnid parasite (name 33) whose sores have unpretentious or no yellowing by any stretch of the imagination (Figurers 4.9.2(b) and 4.9.2(c). [7].

These outcomes recommend that, like human choices, CNNs separate a component of a sore from a picture and explicitly allot a positive score to diseases with a comparative aggregate. On the whole, semantic word references applied to the penultimate layer of CNN can feature the highlights that are often utilized for disease determination as a sensible and interpretable data.

4.10 Discussion

In this investigation, we assessed a variety of perception techniques to decipher the portrayal of plant diseases that the CNN has analyzed. The test results show that some straightforward methodologies, for example, innocent representation of the concealed layer output, are inadequate for plant disease perception, though a few best in class approaches have possible viable applications. Highlight representation and semantic word reference can be utilized to extricate the visual highlights that are vigorously used to characterize a specific disease.

By and by, the choice of the representation viable layer is to a great extent significant. Indeed, even the clarification map, produced for the sore identification of plant diseases, shockingly shows the qualities not the same as those in the first writing in light of the distinctions in the organization engineering and the dataset. In this way, we proposed to picture each layer and examine which layer is generally reasonable for perception.

The correlation of perception strategies featured the most obvious injuries inside each picture. Utilizing datasets joined with explanation names for districts of the injuries, which are frequently made for semantic segmentation assignments, empowers the assessment of explicitness and affectability of the particular techniques by subjective measurements. In any case, CNN may zero in on the highlights that we don't anticipate. In such cases, cautious choices on whether such highlights have physiological essentialness should be made to keep away from over fitting or dataset inclination. On the whole, the perception of CNN shows the likelihood to open the black box of profound learning.

The obstructions to utilizing profound learning strategies decline each year; in any case, it is significant for plant researchers to choose the reasonable organization models and decipher the out coming results.

The representation is powerful to comprehend what the profound organization realizes and it adds to the improvement of the organization design, for example, model determination and boundary decrease.

Our outcomes demonstrate that regardless of whether the perception strategies produce significant outcomes, people actually assume the main part in assessing the representation results by associating the PC created results with proficient information, for instance, in plant science. Our examination, which reveals the qualities of representation strategies for disease analysis, opens another way to create a work process for plant science contemplates, where PCs and plant researchers helpfully work to comprehend the science of plants through machine/profound learning models.

CHAPTER 5

SUMMARY AND IMPLICATION FOR FUTURE RESEARCH

5.1 Summary of the Study

It shows how an example of plant diseases using the CNN model can be expected in the picture from the customized dataset (prepared data set) in the field and past information index. This provides some of the following knowledge of the expectations of plant leaf disease. Since the most extreme kinds of plant leaves are covered under this framework, the rancher may become acquainted with the leaf that was not developed and drills through all conceivable plant leaves. Additionally, this framework mulls over the previous creation of information which will assist the rancher with getting understanding into the interest and the expense of different plants in market.

5.2 Conclusions

Little ranchers are subject to timely and exact harvesting conditions in order to prevent misfortunes. In this inquiry, a pre-prepared CNS was adjusted, and the model was also sent on the web. The eventual result was a request to identify a plant disease. This is free, easy to use and only requires a PDA and web-related partnership. The customer's needs were therefore satisfied as described in this paper. A thorough examination revealed the model's capacity and limitations. Usually an exactness of 93 percent is introduced when approved in a controlled climate. This accuracy is based on several components, which also include object synthesis phase, disease type, and basic information. This would necessitate a series of customer rules for enterprise use, to ensure the expressed precision is transmitted. The best way to embody these highlights is when the model is prepared using a plain foundation and a solitary leaf. Enlargement and transformation of learning have proven to be beneficial to the model, which has helped CNN to summarize further reliability. Although this increased the ability of the model to retrieve highlights r, the symbolism of the model 'in the field' was insufficient.

For this situation, the classifier positioned an accuracy of only 46% above every one of, this Features the significance of enhancing the preparation dataset to incorporate elective foundation information, extra plant life structures and fluctuating phases of disease. Generally speaking, this investigation is definitive in exhibiting how CNNs might be applied to engage little holder ranchers in their battle against plant disease. Later on, work ought to be centered on differentiating preparing datasets and furthermore in testing comparative web applications, in actuality, circumstances.

5.3 Recommendations

There are so many progression steps through large information research that the effects of various understudy exercises without study can be detected. CNN is the ultimate destiny of this world. CNN is the main component of artificial intelligence. Thus, CNN is essential for the development of current frameworks to deal with our issues. In CNN, the classification of information has a greater impact. Classifier of information in the CNN shall be necessary. Classifier of Information may change the idea of the previous gadget understandings-

- Use more data from pictures.
- It helps to make a deeper layer classification.
- More analysis of the convolution layer gets more precise.
- This sector should be focused on by technologists and authorities.

5.4 Implication for Further Study

Agricultural divisions must robotize qualification measure recognition of field crops. The web application or the application in the area of work can be shown in order to computerize this cycle. To improve the work to be done in the environment of artificial intelligence.

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APPENDIX

Research Refection

During project activities, we faced several problems. But three problems were major among them. In this paper, we recognized a portion of the significant issues and inadequacies of works that utilized CNNs to consequently distinguish crop sicknesses. We likewise gave rules and strategies to continue to boost the capability of CNNs conveyed in true applications. Some generally distributed arrangements dependent on CNNs are not at present operational for field utilize for the most part because of an absence of adjustment to a few significant ideas of AI. This absence of similarity may prompt helpless speculation abilities for new information tests as well as imaging conditions, which brings down the useful utilization of the prepared models. By the by, the contemplated works show the capability of profound learning methods for crop infections identification. Their discoveries are unquestionably encouraging for the advancement of new farming instruments that could add to a more manageable and secure food creation.

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