# PLANT DISEASE DETECTION USING IMAGE PROCESSING CNN TECHNOLOGY

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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**DHAKA, BANGLADESH**

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# APPROVAL

This Project titled **“'Plant' Disease Detection Using Image Processing - Pepper, Rice, Tomato, Rice, Potato, Malabar Spinach”** submitted by Shah Md. Iktakhairul Islam, ID: 171-15-8606 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 **September 2019**.

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## DECLARATION

We 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.

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# ABSTRACT

Our Project titled ‘PLANT DISEASE DETECTION USING IMAGE PROCESSING CNN TECHNOLOGY’ deals with disease detection for Potato, Pepper and Tomato, Rice, Malabar Spinach based on image processing. An enormous improvement has been made in the field of picture preparing and AI and its application in different parts of designing. We have entered the time of digitization. We have caught pictures with the assistance of advanced camera. All the more clear the pictures are better and productive the outcomes. In this report we have done the arrangement of sickness free, somewhat infected and totally sick leaves. We have utilized HSI shading model for grouping of our properties and further we have utilized Neural Network Toolbox for AI and investigating the outcomes. The measurement of plant features is a fundamental element of plant science research and related applications. The information related to plant features is especially useful for its applications in plant growth modeling, agricultural research and on farm production. Traditional direct measurement methods are generally simple and reliable, but they are time consuming, laborious and cumbersome. In contrast, the proposed vision-based methods are efficient in detecting and observing the exterior disease features. In the present investigation, image processing algorithms are developed to detect disease by identifying the color feature of the defected area. Subsequently, the rotted area was segmented from an image and area of rotted leaf portion was deduced from the Pepper and tomato plant feature data. The results showed a promising performance of this automatic vision-based system we found 94% accuracy average in practice with easy validation.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

By 2050, worldwide harvest creation should increment by at any rate half to help the predicted request. Most of creation presently happens in Africa and Asia, where 83% of ranchers are family run with practically no agricultural ability. Because of this, yield misfortunes of more noteworthy than half; because of vermin and diseases are basic. In characterizing crop diseases, the customary technique for human examination by visual investigation is not, at this point possible. The advancement of PC vision models offers a fast, normalized and exact answer for this issue. When prepared, a classifier can likewise be conveyed as an application. Simple to use, everything necessary is a web association and camera equipped cell phone. Mainstream business applications 'iNaturalist' and 'PlantSnap' exhibit how this can be executed. Both applications have accomplished achievement in not just conveying mastery to clients yet additionally in building an intuitive on the web social network. Every year, cell phones keep on getting more available and reasonable. In 2020 there are around 5 billon cell phone clients on the planet. Of this, one billion clients are situated in India and a further one billion are found in Africa. As indicated by Statista, these figures have reliably risen each year for the most recent decade. With these realities as a main priority, it is accepted that AI applications will play a significant job in molding the eventual fate of cultivating.

The utilization of CNNs in plant disease arrangement has accomplished superb outcomes as of late. Due to the continuous rise of predominant outcomes, the multi-layered administered network has gotten positive among specialists. Since the arrival of LeNet (1988), CNN structures have changed significantly. Complex capacities, for example, ReLu nonlinearity and covering pooling, have become a pervasive element in present day design. Such advancements have assisted with lessening preparing time and mistake rate. Most importantly, the advancement of engineering has been a fundamental interest of enormous and complex 21st century datasets.

One ongoing design; ResNet (2015) presented further weighty capacities. This fuses dynamic skip associations just as weighty bunch standardization. This permits preparing to happen at a lot higher learning rate. In 2019, Wu et al., contrasted ResNet with VGGNet, GoogLeNet, and DenseNet, finding that ResNet delivered the best outcomes in ordering grape leaf diseases. In current exploration; architectures including AlexNet, LeNet and GoogleNet (2014), are ordinarily fused into the foundation of custom forms. Wallelign proposed such a construct; in light of LeNet, in his examination of Soybean disease order. The model comprised of three convolution layers, one max-pooling layer and a completely associated MLP with Relu actuation and accomplished a 99% accuracy rate. [1]

Information pre-preparing is significantly critical to a model's execution. Viral, bacterial and contagious diseases can be hard to recognize, regularly sharing a cover of indications. These manifestations can be any quantifiable contrast in shading, shape or capacity which result as the plant reacts to the microbe. In light of this multifaceted nature, it is desirable over use RGB information. This produces clear, commotion free pictures which may take longer than greyscale information to prepare, yet generally speaking are more appropriate for plant disease distinguishing proof models.

More modest datasets or unvaried information can influence a model's dependability. This can be overseen severally, by utilizing procedures, for example, growth or move learning. Enlarging preparing pictures cannot just decrease overfitting yet, can improve a model's general execution. This can be performed by adding capacities, for example, zoom, pivot, adding shading changes or differentiation changes. The changed pictures should, nonetheless, mirror the assumptions of the approval dataset. When improperly applied, a classifier's accuracy can deteriorate notwithstanding the additional information created.

The strategy for move learning has additionally demonstrated very fruitful when working with more modest datasets. This includes adjusting the loads of a pre-prepared model. The ImageNet information base is normally utilized for this reason and contains over 14 million pictures.

In 2016, Mohanty et al. uncovered these benefits in an examination zeroed in on harvest disease arrangement. Here, unrivaled outcomes were recorded utilizing move learning (ImageNet), contrasted with a model worked without any preparation. As ImageNet contains pictures superfluous to a plant explicit assignment, it is flawed whether pre-preparing on an herbal information base all things being equal, may upgrade execution. Ebb and flow research recommends that pre-preparing on ImageNet may sum up better, in any case pre-preparing on a plant explicit assignment may lessen overfitting. These assertions, be that as it may, are uncertain. Due to a nonappearance of enormous organic datasets, the subject is generally neglected. Growth can likewise be applied to pertained models. Because of the information previously achieved by a particularly model nonetheless, the impacts are more prominent when applied to un-prepared CNNs. The quality and sort of preparing information enormously impacts the model's abilities. At the point when prepared on symbolism which contains plain foundation information, a classifier's accuracy gets subject to this creation. In this manner, it is prone to be untrustworthy when tried with in-field photography. A considerable lot of the accessible plant disease datasets including, the 'PlantVilllage' dataset, don't contain in-field symbolism. [2] The requirement for such a dataset is featured intensely in examination.

Segmentation for this situation can demonstrate successful, by isolating a leaf from its experience. This strategy can besides be utilized in circumstances where the classifier requires scene mindfulness. For instance, this may include understanding the degree of microbe harm around the tainted tissue, instead of simply the contaminated tissue. Segmentation is certainly not another idea and has been applied to disease grouping undertakings since the 1990s. Indeed, even at this early stage, great outcomes were accounted for. Early examinations were moreover supportive in distinguishing the restrictions, demonstrating that the strategy couldn't beat helpless picture quality. Accordingly, focusing on the significance of cautious information assortment and preprocessing. The pertinence of segmentation proceeds into 2020. There is a lot of examination potential in joining this with particular symbolism.

The kind of preparing information utilized likewise figures out what stage of disease, location is conceivable. For early disease recognition, explicit symbolism should be utilized.

Chlorophyll fluorescent (CFI), infrared thermography (IRT), hyperspectral (HSI) and multispectral (MSI) symbolism have explicit capacities to distinguish manifestations which are not yet noticeable to the unaided eye. These can be utilized alone or joined where suitable. For model, IRT has the remarkable capacity to recognize an expansion in temperature. This has been effective in diagnosing crop diseases remembering fleece mold for roses and FHB in wheat, days before indications were noticeable. This subject of early location is moderately neglected due to the restricted accessibility of such information. The innovation expected to catch this particular symbolism is getting more moderate, with a developing scholastic premium in the region. At this stage in any case, it's anything but an available instrument for distant ranchers. Accordingly, it is ridiculous to remember it for an undertaking expected for such clients. [1]

## 1.2 Motivation

Bangladesh is quick developing nation and agriculture is the spine for the nation's advancement in the beginning phases. Because of industrialization and globalization ideas the field is confronting obstacles. On top of that the mindfulness and the need of the development should be ingrained in the psyches of the more youthful age. Presently a day's innovation assumes indispensable part in all the fields yet till today we are utilizing some old procedures in agriculture. Recognizing plant disease wrongly prompts immense loss of yield, time, cash and nature of item. Distinguishing the state of plant assumes a significant part for effective development. In times past identification is done physically by the accomplished individuals however because of the countless ecological changes the expectation is getting intense. So we can utilize picture handling methods for recognizable proof of plant disease. By and large we can notice the indications of disease on leafs, stems, blossoms and so forth so here we use leafs for identification of disease influenced plants.

## 1.3 Rationale 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 reasonings. The idea of reasonings 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 reasonings being more certainly grouped than 'pseudo'- cases from which these reasonings had been stripped. This methodology significantly beat gauge SVM variations that don't adventure such reasonings. Yessenalina et al. (2010) later built up a way to deal with produce reasonings. A different line of related work concerns models that exploit double oversight, i.e., marks on individual highlights. This work has to a great extent included embeddings imperatives into the learning cycle that favor boundary esteems that line up with from the earlier featurelabel affinities or rankings (Druck et al., 2008; Mann and McCallum, 2010; Small et al., 2011; Settles 2011). We don't examine this profession further here, as our attention is on abusing given reasonings, instead of individual marked highlights.

## 1.4 Expected Output

Expected outcome of this research- based project:

- Detect Disease with 90% above accuracy.
- There will be shown with graph that shown the effected level.
- There will be output a predicted disease type or healthy plants species.

## 1.5 Report Layo

In **chapter 1:** In this section we can examine as respects the Introduction, Motivation then Objectives and furthermore talk about as respects the Expected Outcome, etc is examined quickly. In a word, part 1 is elaboration of presentation of this venture.

In **chapter 2:** In this section we had introduced about the essential state of our work and talk over statute in the venture. We likewise present concerning the connected deals with this territory which were examined are appeared. Their discoveries and constraints are summed up and consequently the extension and difficulties of the examination are likewise referenced.

In **chapter 3:** In this part we discussed research approach talks about examination subject and instrumentation, information assortment strategy, factual investigation and execution prerequisites.

In **chapter 4:** Trial results and conversation Experimental Results and Descriptive Analysis are introduced.

In **chapter 5:** In this part we showed the exhibition of the whole undertaking. Presents a short end, and rundown of references.

In **Chapter 6:** In this last section we gave the last judgments with respect to the epilog of the whole task.

# CHAPTER. 2
# BACKGROUND

## 2.1 Introduction

Technology makes our life so fast and easy where we want everything in our touch. In this chapter, we will discuss related research or project about data classifier which is related to Deep Learning. The whole strategy of building up the model for plant sickness acknowledgment utilizing profound CNN is portrayed further in detail. The total process is separated into a few vital stages in subsections beneath, beginning with social affair pictures for classification process utilizing profound neural networks. In the first section we will discuss about previous related work, then in the second section we will show the outcome or a summary of my study of the related work and then we will discuss about the benefits and challenges that we face to do this project.

## 2.2 Related Works

Kim (2014) proposed the fundamental CNN model we depict beneath and afterward expand upon in this work. Properties of this model were investigated exactly in (Zhang and Wallace, 2015). We likewise note that Zhang et al. (2016) stretched out this model to together oblige various arrangements of pre-prepared word embeddings. Generally simultaneously to Kim, Johnson and Zhang (2014) proposed a comparative CNN engineering, in spite of the fact that they traded in one-hot vectors set up of (pre-prepared) word embeddings.

A Chowdhury, Dhruba K. Bhattacharyya, Jugal K. Kalita propose a Co-Expression Analysis of Gene Expression: A Survey of Best Practices. It introduced an outline of best practices in the examination of (differential) co-articulation, coexpression 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 frog-bouncing 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, SaiMaungMaungZaw proposed Plant Diseases Recognition for Smart Farming Using bModelbased Statistical Features. Ithas 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 considered as energy supply to humanity. Plant diseases can influence the agriculture which can be come about in to colossal misfortune on the harvest yield. Consequently, leaf diseases identification assumes an essential part in agricultural field. Nonetheless, it requires enormous labor, additionally handling time and broad information and aptitudes about plant diseases. Subsequently, AI comes in play in the discovery of diseases in plant leaves as it dissects the information from different territories, and characterizes it into one of the predefined set of classes. The highlights and properties like tone, force and measurements of the plant leaves are considered as a significant actuality for arrangement and the different kinds of plant diseases and diverse characterization methods in AI that are utilized for distinguishing diseases in various plants leaf. It this investigation intends to assess the utilization of a pre-prepared ResNet34 model in preparing a plant disease classifier. Three plant species will be centered on.

These incorporate potato (Solanum tuberosum), tomato (Solanum lycopersicum) and rice (Oryza sativa). For every species the model will be prepared to perceive a select number of diseases or condition of strength.

The particular objectives of this exploration are to:

I. Determine the model's general viability in characterizing diseases utilizing both an approval and test dataset.
II. Compare the model's accuracy when tried with different picture sizes and enlargement settings.
III. Deploy the prepared model to make a simple to utilize web application.

Because of a lopsided class dispersion, both the f1-score and accuracy measurements will be inspected in getting to the model's exhibition. When the model arrives at an accuracy and F1score of more noteworthy than 80%, it will be acknowledged.

This exploration will be completed in view of the requirements of smallholder ranchers. The classifier and web application will require both a cell phone and web association, which as recently referenced, keep on arriving at far off areas. In recognizing the constraints of essential camera telephones, the model will be tried with an assortment of picture sizes and growth settings. We have stayed cautious can't about terrible accuracy and yield. By utilizing measurements, we have great accuracy range to locate the most ideal correlation.

## 2.4 Scope of the 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.

## 2.5 Challenges

### 1) Data Collection

More modest datasets or unvaried information can influence a model's unwavering quality. This can be overseen severally, by utilizing procedures, for example, expansion or move learning. Increasing preparing pictures can diminish overfitting as well as can improve a model's general execution. The quality and sort of preparing information hugely impacts the model's abilities. At the point when prepared on symbolism which contains plain foundation information, a classifier's accuracy gets reliant on this structure. Consequently, it is probably going to be temperamental when tried with in-field photography. A considerable lot of the accessible plant disease datasets including, the 'PlantVilllage' dataset [3], and furthermore added an enormous number of pictures information for better accuracy. Try not to contain in-field symbolism. The requirement for such a dataset is featured intensely in examination.

### Model selection

Model determination is a most significant part and furthermore probably the hardest piece of an exploration project. The accomplishment of any examination depends on Data set and Model determination. On the off chance that we can pick the model effectively, there should be a positive result soon. Then again picking an awful one may prompt disappointment as a definite truth. For this, we have tried a few models with our test information looking for the most reasonable one for our exploration project. In any case, from that whole inquiry, we have arrived at the resolution that Naïve Byes Classifier calculation as the most effortless and the best one for us. At the point when we have discovered that it gives a simple to utilize library, we comprehended that the classifier work would be simpler. Along these lines, we finished this model for our utilization in our undertaking.

### 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 OpenCV 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 Fig 2.5.1, Fig 2.5.2 [1] and Fig 2.5.1.

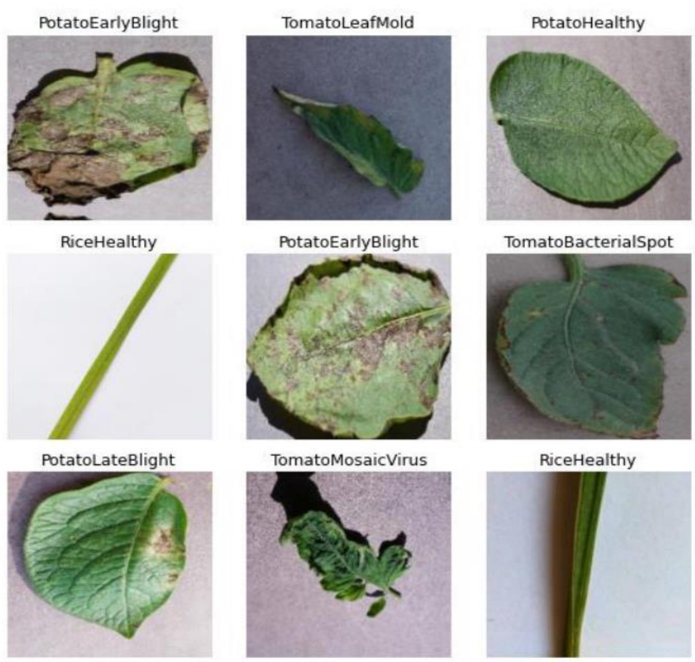


Fig 2.5.1: Pre-Processed Input Data Example Phase One - padding mode (reflection).

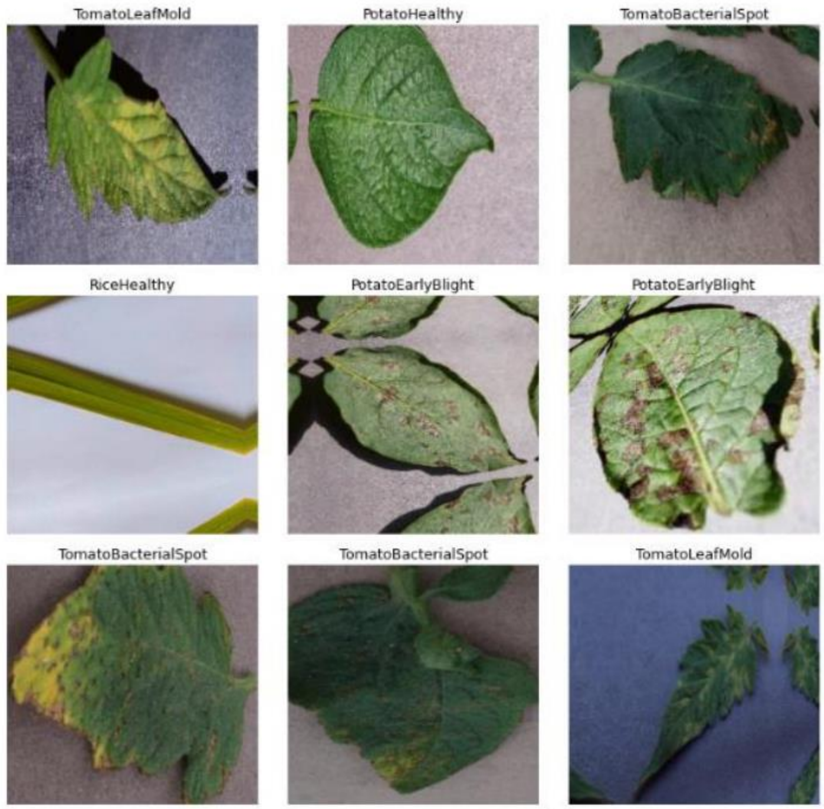


Fig 2.5.2: Pre-Processed Input Data Example Phase Two- brightness changes (0.4, 0.7).

Fig 2.5.3: Pre-Processed Rise Leaf Input Data Example Phase One.

# CHAPTER 3

# RESEARCH METHODOLOGY

## 3.1 Introduction

Research methodology used to recognize select, measure and investigate data. Presently in this part we will examine and portray about our examination technique. Additionally, apparatuses for the exploration project, information assortment, research subject, pre-handling, preparing, factual examination, and its execution will be talked about in this session.

## 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.

**Stap 1(a): 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 Fig 3.2 [5]

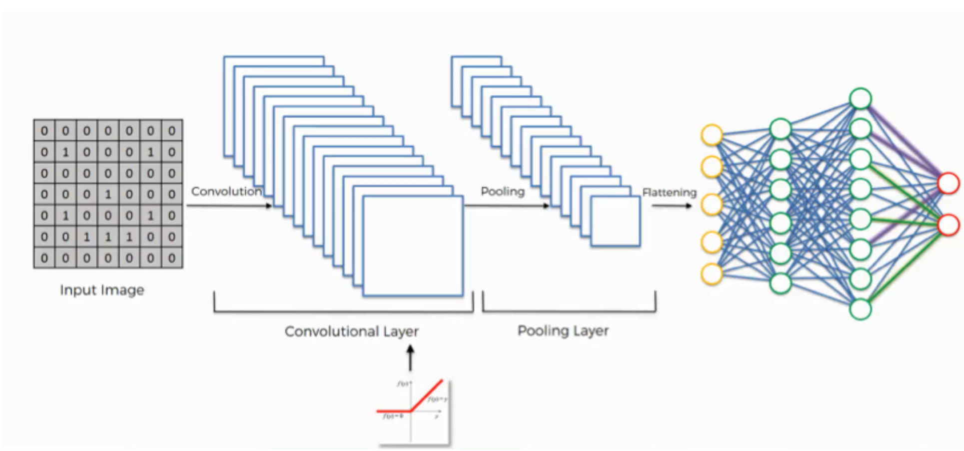


Fig 3.2: Image Classification steps with CNN

**Step 1(b): 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.

Redundant for understanding CNN's, but rather there's no mischief in a brisk exercise to improve your aptitudes.

**Stage 2: Pooling**

In this part, we'll cover pooling and will see precisely how it by and large functions. Our nexus here, in any case, will be a particular sort of pooling; max pooling. We'll cover different methodologies, however, including mean (or total) pooling. This part will end with an exhibition made utilizing a visual intelligent apparatus that will figure the entire idea out for you.

**Stage 3: Flattening**

This will be a short breakdown of the straightening cycle and how we move from pooled to leveled layers when working with Convolutional Neural Networks.

**Stage 4: Full Connection**

In this part, all that we covered all through the segment will be consolidated. By learning this, you'll will imagine a fuller image of how Convolutional Neural Networks work and how the "neurons" that are at last created become familiar with the arrangement of pictures.

Synopsis: Eventually, we'll wrap everything up and give a fast recap of the idea canvassed in the part. In the event that you feel like it will do you any profit (and it presumably will), you should look at the additional instructional exercise in which Softmax and Cross-Entropy are covered. It's not compulsory for the course, but rather you will probably run over these ideas when working with Convolutional Neural Networks and it will do you a ton of good to be acquainted with them. SoftMax and Cross-Entropy: Some extra to improve your comprehension of Convolutional Neural Networks. Are you game? How about we begin!

## 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

We collect and make an image data bundle that's effects of several thousands of image of Pepper, Tomato, Malabar Spinach, Rice etc. More modest datasets or unvaried information can influence a model's unwavering quality. This can be overseen severally, by utilizing procedures, for example, expansion or move learning. Increasing preparing pictures can diminish overfitting as well as can improve a model's general execution. The quality and sort of preparing information hugely impacts the model's abilities. At the point when prepared on symbolism which contains plain foundation information, a classifier's accuracy gets reliant on this structure. Consequently, it is probably going to be temperamental when tried with in-field photography. A considerable lot of the accessible plant disease datasets including, the 'PlantVilllage' dataset [3], and furthermore added an enormous number of pictures information for better accuracy. Try not to contain in-field symbolism. The requirement for such a dataset is featured intensely in examination.

Fitting datasets are needed at all phases of article acknowledgment research, beginning from preparing stage to assessing the exhibition of acknowledgment calculations. Thirteen classes spoke to plant diseases which could be outwardly decided from leaves.

To recognize solid leaves from diseased ones, one more class was added in the dataset. It contains just pictures of solid leaves. An additional class in the dataset with foundation pictures was advantageous to get more precise order. The foundation pictures were taken from the Stanford foundation dataset [3].

In this stage, all copied pictures taken from various sources were eliminated by created python content applying the looking at method. The content eliminated the copies by looking at the pictures' metadata: name, size, and the date. After the computerized expulsion, pictures were surveyed by human specialists in much emphasis.

Subsequent stage was to enhance the dataset with increased pictures. The principle objective of the introduced study is to prepare the organization to get familiar with the highlights that recognize one class from the others. In this way, when utilizing more enlarged pictures, the possibility for the organization to become familiar with the fitting highlights has been expanded. At long last, an information base containing around 24500 pictures for preparing and 12589 pictures for approval has been made. The growth cycle is depicted in 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 14000 pictures. Here, to foresee the diseases. We provided a sample input preprocessed image on Fig 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 colab 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 CoLab. Some process is given below Fig 3.4.1.

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

```
Mounted at /content/drive
```

Fig 3.4.1: Data importing by Colab python3.8

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

```python
EPOCHS = 25
INIT_LR = 1e-3
BS = 32
default_image_size = tuple((256, 256))
image_size = 0
directory_root = '/content/drive/My Drive/Colab Notebooks/PlantVillage/'
width=256
height=256
depth=3
```

Fig 3.4.2 : Resize and format of image data by Python3.8

### 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 (Kernals), 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 Fig: 3.3.

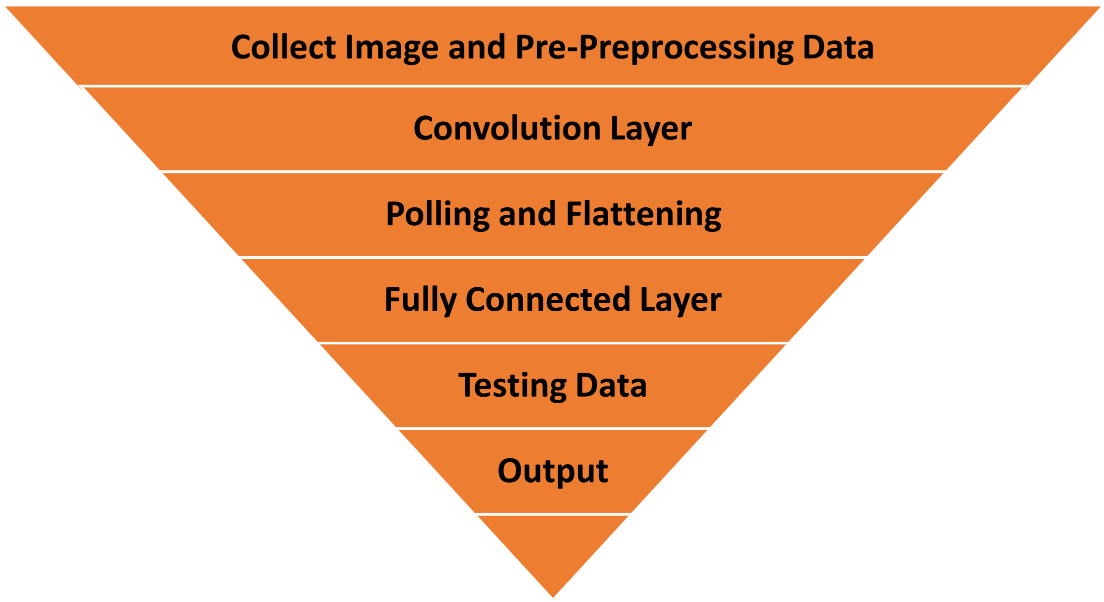


Fig 3.4.3: Image Classification steps and data processing

## 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.

**Table 3.1 :** Image data amount

TABLE I: DATASET USED FOR CLACIFICATION

| **Species** | Class | No. of Images |
|---|---|---|
| Pepper | Pepper Bell | 997 |
| Pepper | Healthy | 1478 |
| Potato | Early blight | 986 |
| Potato | Late blight | 989 |
| Potato | Healthy | 145 |
| Tomato | Bacterial Spot | 2115 |
| Tomato | Leaf Mold | 540 |
| Tomato | Mosaic Virus | 155 |
| Tomato | Healthy | 990 |
| Rice | Brown Spot | 510 |

| | | |
|---|---|---|
| Rice | Leaf Blast | 775 |
| Rice | Healthy | 998 |

## 3.6 Implementation 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 RESULTS 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 Potato and Tomato symbolism get from 'The PlantVilllage Dataset', an open-access store which contains altogether 54,323 pictures. All Rice symbolism begins from the "Rice Diseases Image 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, in-field foundation information and fluctuating phases of disease.

TABLE I I: FINAL DATASET USED FOR CLACIFICATION

| **Species** | Class | No. of Images |
|---|---|---|
| Pepper | Pepper Bell | 997 |
| Pepper | Healthy | 1478 |
| Potato | Early blight | 986 |
| Potato | Late blight | 989 |
| Potato | Healthy | 145 |
| Tomato | Bacterial Spot | 2115 |
| Tomato | Leaf Mold | 540 |
| Tomato | Mosaic Virus | 155 |
| Tomato | Healthy | 990 |
| Rice | Brown Spot | 510 |
| Rice | Leaf Blast | 775 |

| | | |
|---|---|---|
| Rice | Healthy | 998 |

## 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 [3]. The settings applied incorporate flipping (arbitrary), cushioning mode (reflection) and zoom with crop (scale = (1.0, 1.5)). 'Zoom with crop' was later overlooked subsequent to finding that it had improperly trimmed zones of contaminated leaf. At last, all pictures are re-sized and standardized. Resizing is completed utilizing a pack work, to 256 x 256. As a pre-prepared model is utilized, the RBG ImageNet measurements are utilized to standardize. An example of the last pre-handled pictures is perceptible in Fig.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. 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 Fig.2.5.1. All means stay predictable in every preliminary including the learning rate. And the convolutional Operation processing in the Fig.4.4. [5]

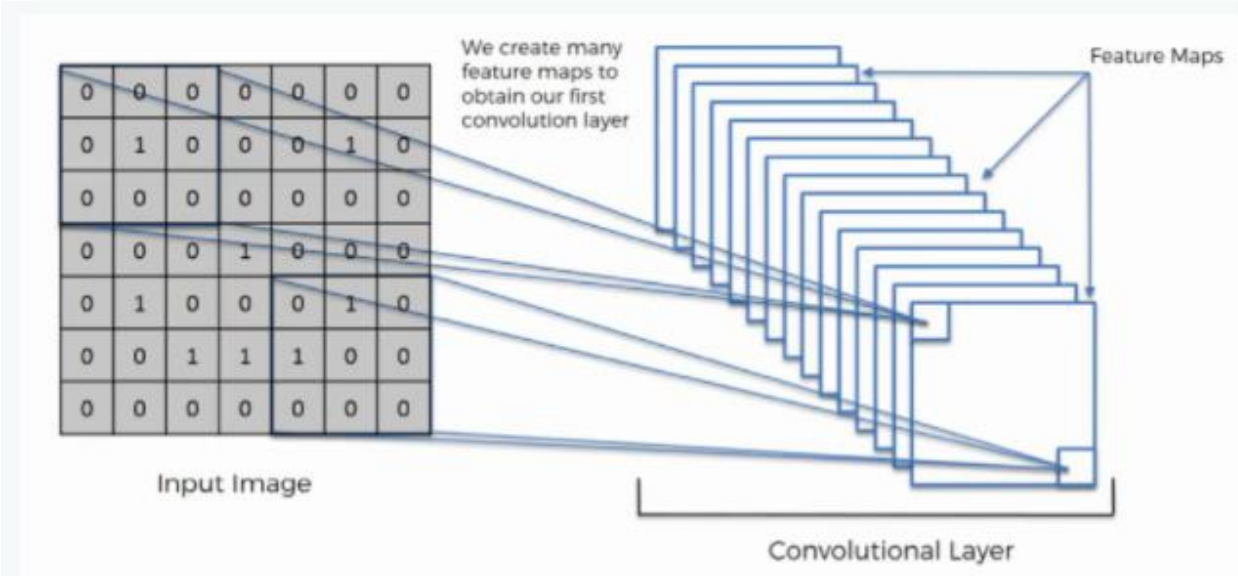


Fig 4.4: Input image processes by convolutional layer

2) 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 (Fig. 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 Fig 4.5.1. [5]

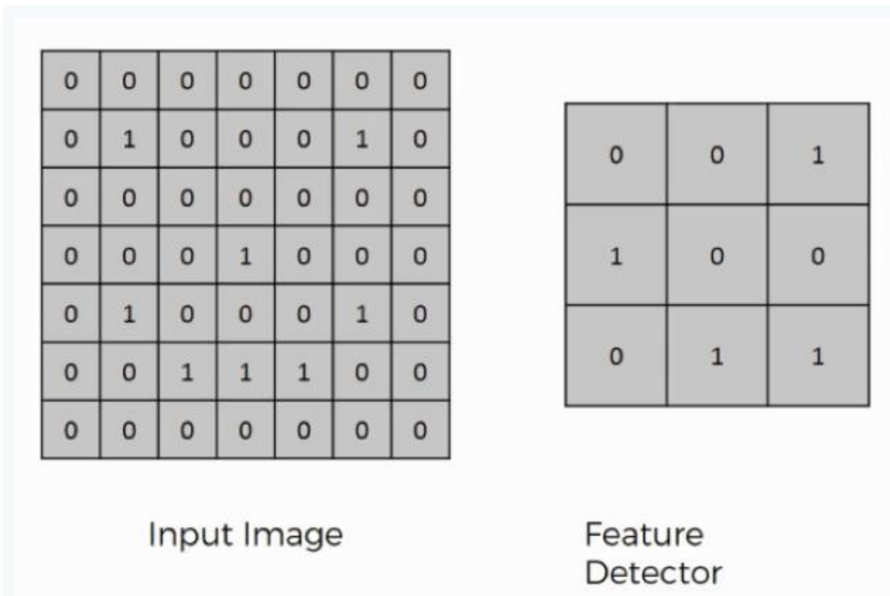


Fig 4.5.1: The Convolutional Operation

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 Fig 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.

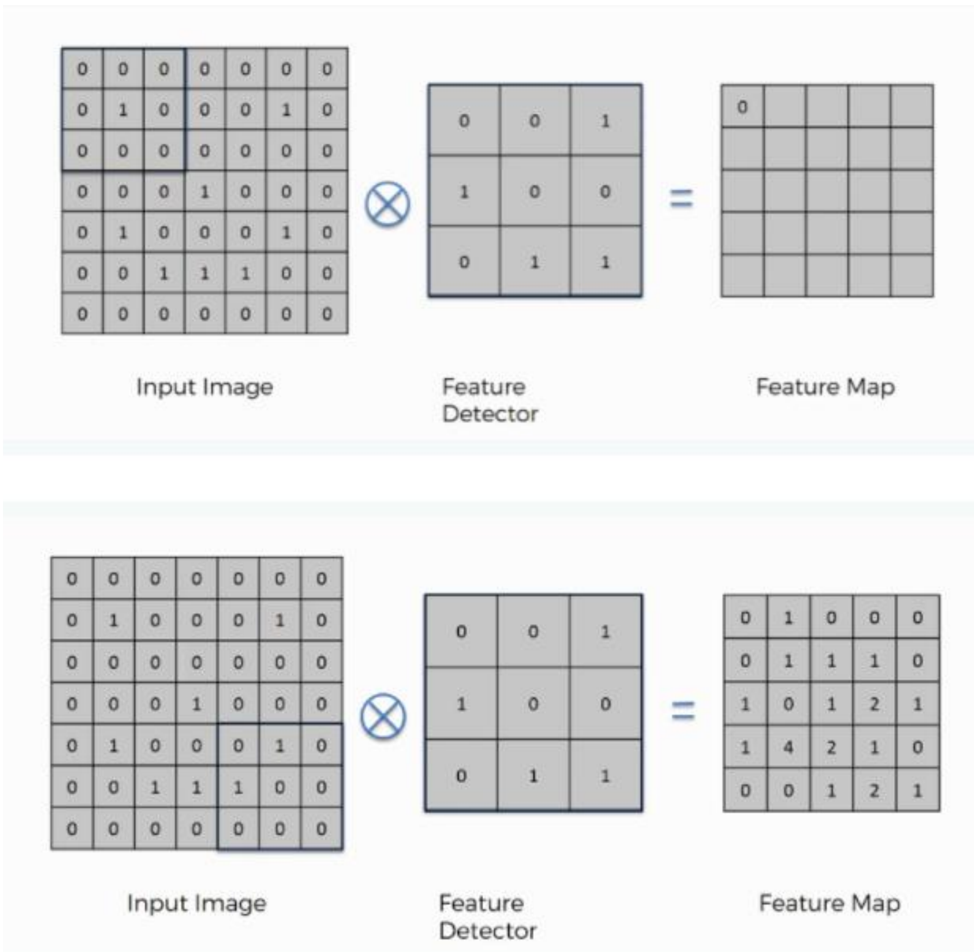


Fig 4.5.2: The Convolutional Operation

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’s 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 Fig.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

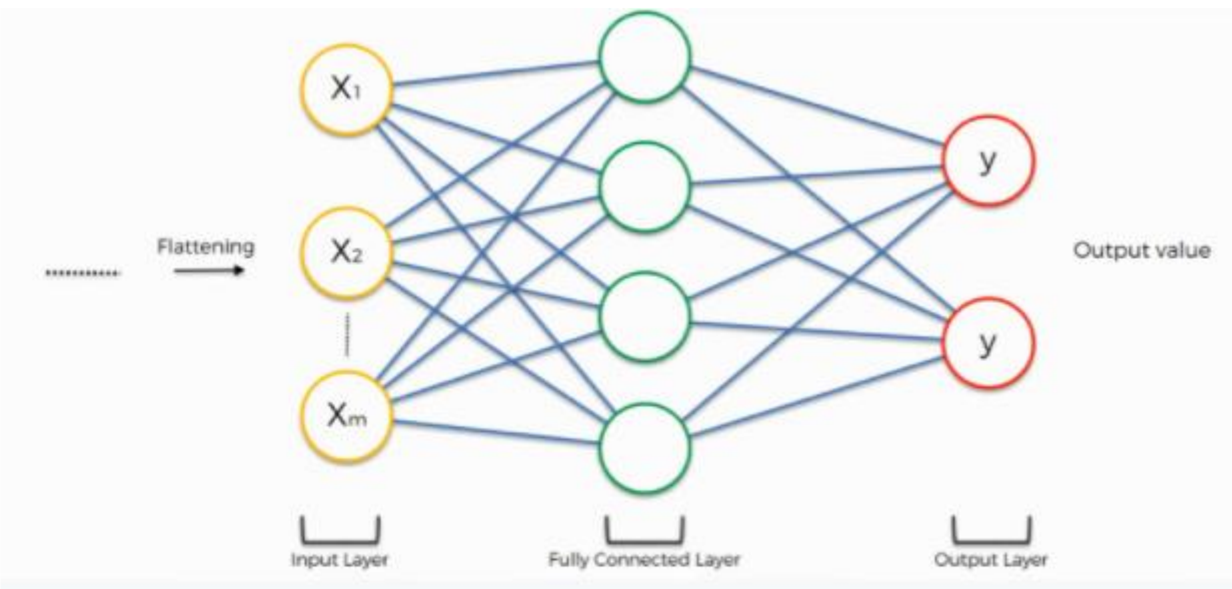


Fig 4.6: The Convolutional Full Connection

## 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 94% accurate.

## 4.8 Effect of result Phase Two

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

```
model = Sequential()
inputShape = (height, width, depth)
chanDim = -1
if K.image_data_format() == "channels_first":
    inputShape = (depth, height, width)
    chanDim = 1
model.add(Conv2D(32, (3, 3), padding="same",input_shape=inputShape))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=chanDim))
model.add(MaxPooling2D(pool_size=(3, 3)))
model.add(Dropout(0.25))
model.add(Conv2D(64, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=chanDim))
model.add(Conv2D(64, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=chanDim))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Conv2D(128, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=chanDim))
model.add(Conv2D(128, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=chanDim))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(1024))
model.add(Activation("relu"))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(n_classes))
model.add(Activation("softmax"))
```

Fig 4.8.1: The Convolutional Model Code

Here the test output that we have given is plants leaf with leaf spot Phase Two Model Optimization Analysis on Fig.4.8.2 -

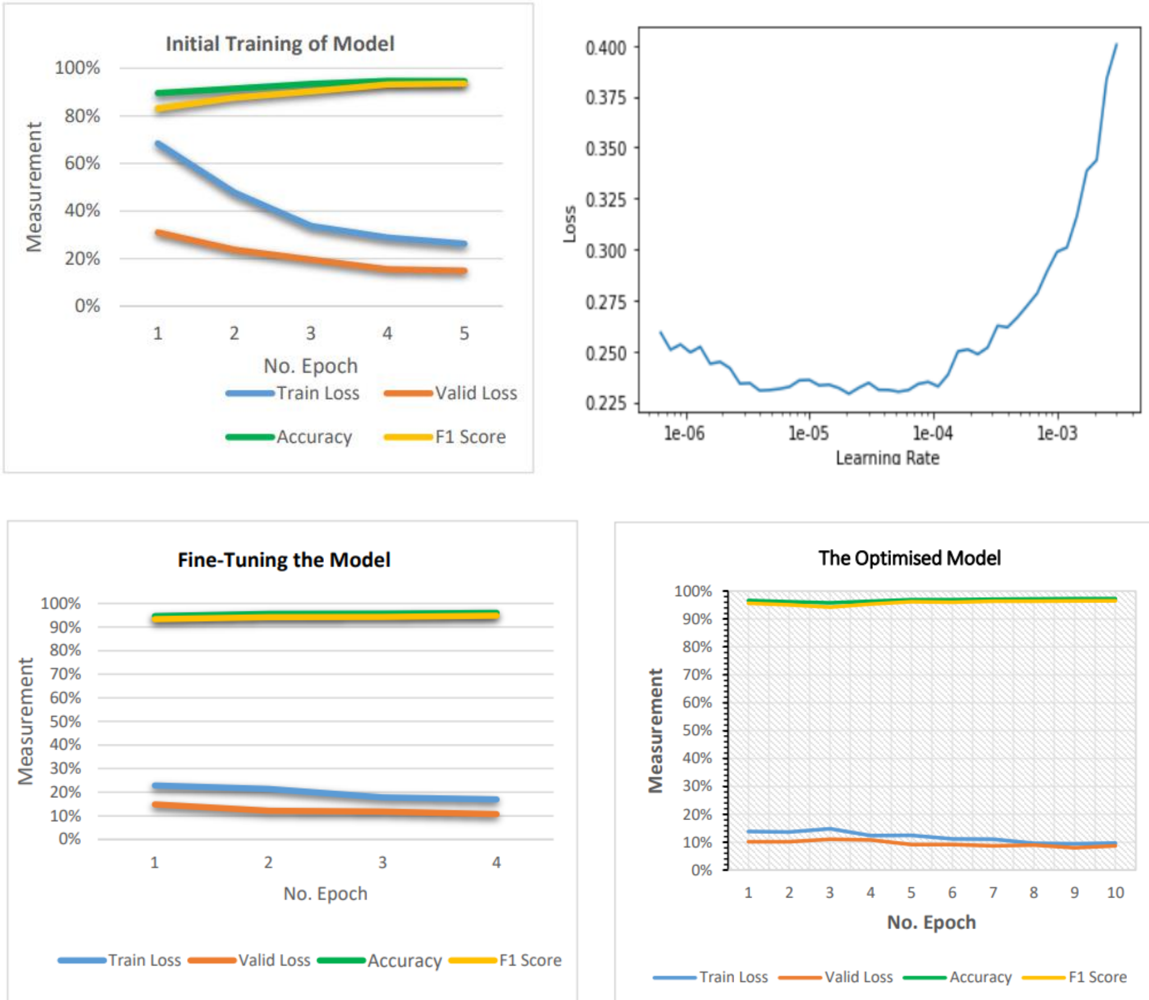


Fig 4.8.2: Plant Leaf Phase Two Model Optimization Analysis

Hear in Fig.4.8.2 as a result analysis we can see the four data measurement figure those are 1) Training the last layers (lr=1e-3) before tweaking the model accomplished an accuracy of 0.9465 and F1 score of 0.9359. 2) 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. 3) Fine-tuning the model, learning rate range = 1e-05, 1e, 04, ages = 4, Signs of under fitting evident. 4) 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. (Fig.4.8.2-1). To help adjusting, a plot portraying learning rate (logarithmic scale) v misfortune was examined (Fig.4.8.2-2).

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 (Fig.4.8.2-3) .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 (Fig.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:**

TABLE I I I.: RESULT – PHASE ONE (4 EPOCHS, MAX_LR (1E-05, 1E-04))

| Test | Image size | Train Loss | Valid Loss | Accuracy | F1 Score |
|---|---|---|---|---|---|
| 1 | 150 | 0.1550 | 0.1243 | 0.9604 | 0.9543 |
| 2 | 185 | 0.1574 | 0.1345 | 0.9422 | 0.9386 |
| 3 | 215 | 0.1775 | 0.1145 | 0.9729 | 0.9657 |
| 4 | 235 | 0.1285 | 0.1045 | 0.9341 | 0.9123 |
| 5 | 256 | 0.1553 | 0.1242 | 0.9532 | 0.9363 |

## 4.9 Phase Three– Visualizations

Figure 4.9.1 envisions the concealed layer output [6] 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.

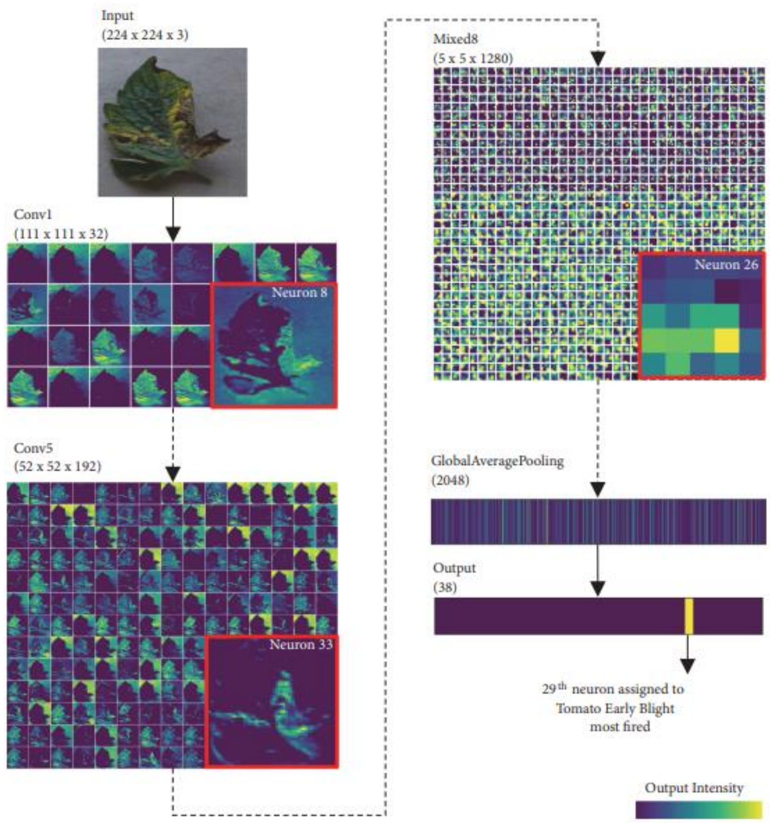


Fig 4.9.1: Plant Disease Visualization of intermediate output.

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 [42] for 200 pictures of tomato early scourge (see Materials and Methods for subtleties of commitment score count). [6]

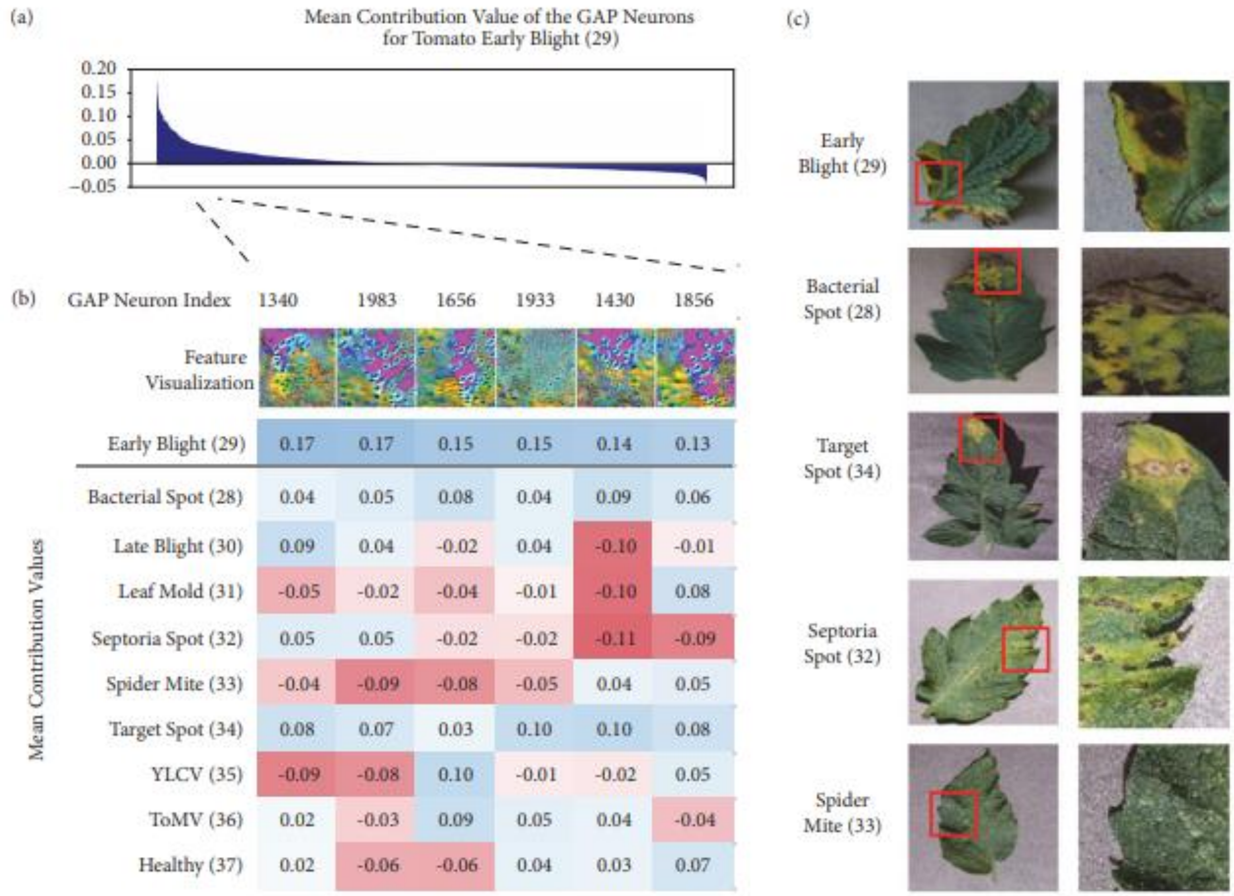


Fig 4.9.2: Plant Disease Visualization of Semantic Dictionary.

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 early scourge (Figures 4.9.2(b) and 4.9.2(c)). Be that as it may, they barely or adversely add to septoria spots (mark 32) and arachnid parasite (name 33) whose sores have unpretentious or no yellowing by any stretch of the imagination (Figures 4.9.2(b) and 4.9.2(c)). [6]

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 overfitting 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 zeroed in how picture from given dataset (prepared dataset) in field and past informational index utilized anticipate the example of plant diseases utilizing CNN model. This brings a portion of the following bits of knowledge about plant leaf disease expectation. As most extreme sorts of plant leaves will be covered under this framework, rancher may become acquainted with about the leaf which may never have been developed and drills down all conceivable plant leaves, it helps the rancher in dynamic of which yield to develop. 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

At to forestall misfortunes, little holder ranchers are subject to an opportune and precise harvest disease finding. In this investigation, a pre-prepared Convolutional Neural Network was adjusted, what's more, the model was sent on the web. The eventual outcome was a plant disease identification application. This administration is free, simple to utilize what's more, requires only a PDA and web association. Consequently, the client's necessities as characterized in this paper have been satisfied. A careful examination uncovered the capacities and constraints of the model. Generally, when approved in a controlled climate, an accuracy of 97.2% is introduced. This accomplished accuracy relies upon various components counting the phase of disease, disease type, and foundation information also, object synthesis. Because of this, a bunch of client rules would be needed for business use, to guarantee the expressed accuracy is conveyed. As the model was prepared utilizing a plain foundation and solitary leaf, impersonation of these highlights is best. Enlargement and move learning for this situation, demonstrated gainful to the model, assisting the CNN with summing up additional dependability. While this improved the model's capacity to extricate highlights r, it was insufficient when the model was given 'in field' symbolism. For this situation, the classifier positioned an accuracy of only 44% 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. Without such turns of events, the battle against plant disease will proceed.

## 5.3 Recommendations

There are so numerous advancement steps can be occurred by large information investigation like discovering effects of different exercises of understudies without study. The eventual fate of this world relies upon CNN. In Artificial Intelligence, CNN is the main part. Thus, utilizing CNN to take care of our issues is basic to the headway of the present creations for creating framework. In CNN, information classifier impacts more significant job. Information classifier must require in the CNN. Information classifier may change the whole idea about the previous understandings with respect to the gadget.

- Using more Images data.
- Making deeper layer classifier will help.
- More Convolution-layer analysis get more accuracy.
- Technologists and authorities need to focus on this sector.

## 5.4 Implication for Further Study

Agricultural division needs to robotize the recognizing the yield crops from qualification measure (genuine time).To computerize this cycle by show the expectation result in web application or work area application. To enhance the work to execute in Artificial Intelligence climate.

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# APPENDIX

## RESEARCH REFLECTION 1

During project activities, we faced several problems. But three problems ware 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.