CHAPTER 1

INTRODUCTION

1.1 Overview

Potato is one of the major harvests in our country. The production of potatoes is hampered by Many kinds of Pests and diseases. So we can’t export potatoes to our expectations in the other countries. Among them early blight, leaf roll virus, scab, Hollow heart etc. are the most terrible disease of potatoes at previous present and times, the major area's farmers faced many hampers on this disease every year [5]. The farmers and businessmen of our country are facing many problems with those diseases particularly in the case of export to other countries.

There are various occupations in the world but majorly agriculture is the primary occupation [3]. India economy not exception to it, which depends on agriculture a lot Potato is the one of the major crop which contributes to about 28.9% of total agricultural crop production in India. Potato is a fourth largest agricultural food crop in the world after maize, wheat and rice. India is a 2nd largest country in the production of potatoes which produces 48.5 million every year [1].

Early detection of these disease can allow to take preventive measures and mitigate economic and production losses [1]. Over the last decades, the most practiced approach for detection and identification of plant diseases is naked eye observation by expert. But in many cases, this approach proves unfeasible due to the excessive processing time and unavailability of experts at farms located in remote areas.

Agriculture is an essential sector in countries like India as those countries’ economy directly or indirectly dependent on agriculture [1]. It indicates the necessity of taking care of plants from seedling until the expected crop obtains. Through this process, the crop needs to cross a lot of phases to obtain the expected crop such as weather conditions, the survival of the crop from various diseases, and the survival of the crop from various animals. Of these major phases, the crops can be protected from the various animals by providing proper protection for the field and this issue can be solvable. The next major issue is weather conditions which will not be in the control of humans, humans can only pray for better weather conditions to obtain a better crop. Finally, the major issue which is very crucial to protect the crop from various diseases

as these diseases can impact the complete growth and yield of the crop. If one can able to identify these diseases in time, then the crop can be protected using appropriate fertilizers. If this process of identification and classification of diseases able to digitalize which would be helpful for the agriculturists [2]. It will decrease the time for the identification of disease and precision in classifying the diseases. There are a lot of significant crops exist in India, one among them is Potato. More than three-fourths of the population of India consumes potato daily at the same time it is one of the popular yielding crops in India. Yet, the yield of the potato crop can be diminished due to various diseases such as late blight and early blight.

These diseases are also known as Phytophthora In festans and Alternaria Solani respectively in scientific terms. Timely identification and classification of these diseases will lead to avoid the yield as well as financial losses [6]. The popular way of identification of these diseases through the utilization of the human eye for decades. But this methodology arises with certain infeasibilities such as overtime will be taken for processing and shortage of experts at fields in remote locations. Therefore, the image analysis turned out to be an efficient methodology that will play a vital role in monitoring as well as the identification of the plant disease conditions effectively. Because the visible patterns are available on the plant leaves and patterns will be identified using various image processing methodologies for obtaining a particular pattern corresponding to a disease which will create an impact in the identification of various diseases. Thus, the obtained features or patterns will be compared with the historical data and able to classify the disease which can be done by using various machine learning methodologies [7].

So, the combination of image processing and machine learning is very effective in the identification and classification of diseases. The present document was structured into various sections such as section-1 introduces the necessity of plant leaves diseases detection using image processing and machine learning methodologies, section -2 deals with the study of previous research based on identification and classification of diseases, precisely, a literature review, section-3 discusses the various methodologies necessary for the detection and classification of plant leaves, section-4 discusses the generated results based on the proposed framework and evaluation metrics, lastly, section-5 generates the conclusion of the presented work and future work based on this framework.

1.2 Problem Statement

Traditional methods for identifying plant diseases are time-consuming and demand specialized knowledge. The need for a more efficient, automated, and accurate approach is evident to minimize crop losses and ensure food security.

Design an effective method to extend the shelf life of potatoes by addressing issues like sprouting and microbial decay, aiming to reduce wastage caused by improper storage practices.

1.3 Significance and Relevance of Work

All through the proposed model, the CNN algorithm is utilized to recognize various kinds of potato infections, having 7 classes of potato sicknesses and accomplished 99% accuracy rate. CNNs thinks about piece by piece of picture. The pieces that CNN looks for are called highlights. It finding the harsh element matches in two pictures in similar positions, CNNs improve at seeing closeness than entire picture coordinating plans. Each component resembles a smaller than normal picture, a little two-dimensional cluster of qualities.

This project mainly focuses on disease detection of potatoes from any surface by using machine learning (CNN). We found that CNN is the best way to perform this type of detection object. However, this model gains 99% of validation accuracy. We have a large amount of data set and to get the best accuracy, we have tried our best. We think this type of project will play a vital role in our agriculture sector. Most of the farmers of the village in India are not literate and they can't know about the disease properly. They can't know the method of detecting disease. That's why the insect is destroying the potato and our farmers get to suffer from it. We think that, this work can change the situation of the potato grower in India.

1.4 Objectives

- ❖ Diagnose potato disease using leaf pictures that we are going to do through advanced deep learning technique.
- ❖ Detect early disease in potato.
- ❖ Implement an automated disease detection system.
- ❖ Improve accuracy in identifying potato diseases.
- ❖ Identify best storage conditions.
- ❖ Monitor storage environments.
- ❖ Asses economic viability.

1.5 METHODOLOGY

Karen Simonyan and Andrew Zisserman proposed the idea of the VGG network in 2013 and submitted the actual model based on the idea in the 2014 ImageNet Challenge. They called it VGG after the department of Visual Geometry Group in the University of Oxford that they belonged to.

So, what was new in this model compared to the top-performing models AlexNet-2012 and ZFNet-2013 of the past years? First and foremost, compared to the large receptive fields in the first convolutional layer, this model proposed the use of a very small 3 x 3 receptive field (filters) throughout the entire network with the stride of 1 pixel. Please note that the receptive field in the first layer in AlexNet was 11 x 11 with stride 4, and the same was 7 x 7 in ZFNet with stride 2[5].

The idea behind using 3 x 3 filters uniformly is something that makes the VGG stand out. Two consecutive 3 x 3 filters provide for an effective receptive field of 5 x 5[8]. Similarly, three 3 x 3 filters make up for a receptive field of 7 x 7. This way, a combination of multiple 3 x 3 filters can stand in for a receptive area of a larger size.

But then, what is the benefit of using three 3 x 3 layers instead of a single 7 x 7 layer? Isn’t it increasing the no. of layers, and in turn, the complexity unnecessarily? No. In addition to the three convolution layers, there are also three non-linear activation layers instead of a single one you would have in 7 x 7[1]. This makes the decision functions more discriminative. It would impart the ability to the network to converge faster.

Secondly, it also reduces the number of weight parameters in the model significantly. Assuming that the input and output of a three-layer 3 x 3 convolutional stack have C channels, the total number of weight parameters will be 3 * 32 C2 = 27 C2. If we compare this to a 7 x 7 convolutional layer, it would require 72 C2 = 49 C2, which is almost twice the 3 x 3 layers [3]. Additionally, this can be seen as a regularization on the 7 x 7 convolutional filters forcing them to have a decomposition through the 3 x 3 filters, with, of course, the non-linearity added in-between by means of ReLU activations. This would reduce the tendency of the network to over-fit during the training exercise.

Another question is – can we go lower than 3 x 3 receptive size filters if it provides so many benefits? The answer is ―No.‖ 3 x 3 is considered to be the smallest size to capture the notion of left to right, top to down, etc. So, lowering the filter size further could impact the ability of the model to understand the spatial features of the image [2].

The consistent use of 3 x 3 convolutions across the network made the network very simple, elegant, and easy to work with.

VGG Configurations

The authors proposed various configurations of the network based on the depth of the network. They experimented with several such configurations, and the following ones were submitted during the ImageNet Challenge.

A stack of multiple (usually 1, 2, or 3) convolution layers of filter size 3 x 3, stride one, and padding 1, followed by a max-pooling layer of size 2 x 2, is the basic building block for all of these configurations. Different configurations of this stack were repeated in the network configurations to achieve different depths. The number associated with each of the configurations is the number of layers with weight parameters in them.

The convolution stacks are followed by three fully connected layers, two with size 4,096 and the last one with size 1,000. The last one is the output layer with Softmax activation. The size of 1,000 refers to the total number of possible classes in ImageNet.

VGG16 refers to the configuration ―D‖ in the table listed below. The configuration ―C‖ also has 16 weight layers. However, it uses a 1 x 1 filter as the last convolution layer in stacks 3, 4, and 5. This layer was used to increase the non-linearity of the decision functions without affecting the receptive field of the layer.In this discussion, we will refer to configuration ―D‖ as VGG16 unless otherwise stated.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 1.1: VGG Configurations

The left-most ―A‖ configuration is called VGG11, as it has 11 layers with weights – primarily the convolution layers and fully connected layers. As we go right from left, more and more convolutional layers are added, making them deeper and deeper. Please note that the ReLU activation layer is not indicated in the table [6]. It follows every convolutional layer.

VGG 16 Architecture

Of all the configurations, VGG16 was identified to be the best performing model on the ImageNet dataset. Let's review the actual architecture of this configuration.

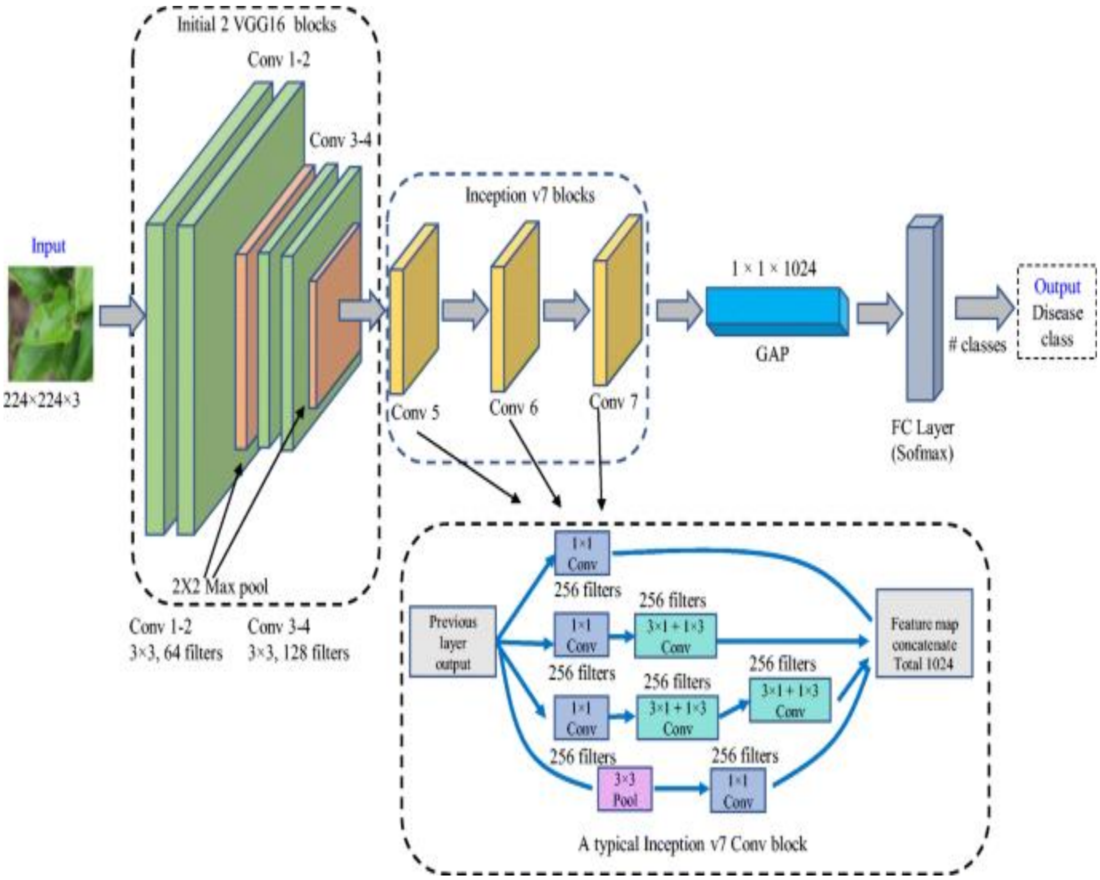
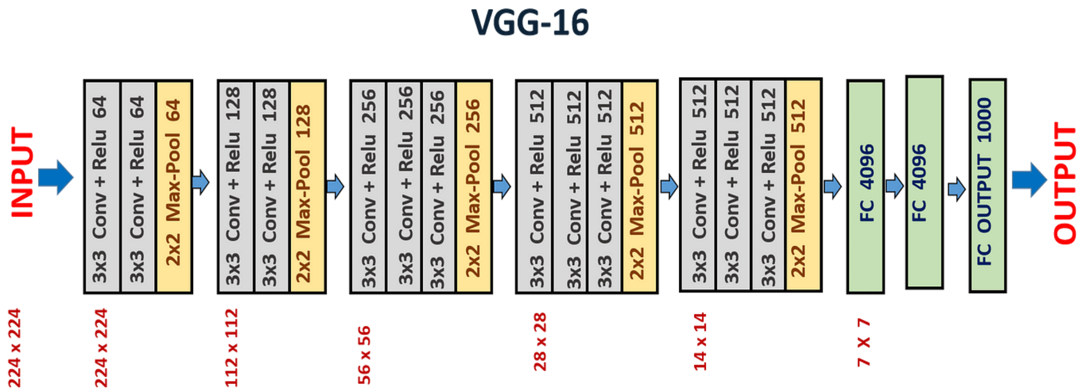


Figure 1.2: VGG-16 Architecture

The input to any of the network configurations is considered to be a fixed size 224 x 224 image with three channels – R, G, and B. The only pre-processing done is normalizing the RGB values for every pixel. This is achieved by subtracting the mean value from every pixel [9].

Image is passed through the first stack of 2 convolution layers of the very small receptive size of 3 x 3, followed by ReLU activations. Each of these two layers contains 64 filters.

The convolution stride is fixed at 1 pixel, and the padding is 1 pixel. This configuration preserves the spatial resolution, and the size of the output activation map is the same as the input image dimensions. The activation maps are then passed through spatial max pooling over a 2 x 2-pixel window, with a stride of 2 pixels. This halves the size of the activations. Thus, the size of the activations at the end of the first stack is 112 x 112 x 64[1]



The activations then flow through a similar second stack, but with 128 filters as against 64 in the first one. Consequently, the size after the second stack becomes 56 x 56 x 128. This is followed by the third stack with three convolutional layers and a max pool layer. The no. of filters applied here are 256, making the output size of the stack 28 x 28 x 256. This is followed by two stacks of three convolutional layers, with each containing 512 filters. The output at the end of both these stacks will be 7 x 7 x 512[1].

The stacks of convolutional layers are followed by three fully connected layers with a flattening layer in-between. The first two have 4,096 neurons each, and the last fully connected layer serves as the output layer and has 1,000 neurons corresponding to the 1,000 possible classes for the ImageNet dataset. The output layer is followed by the Softmax activation layer used for categorical classification.

VGG 19 Architecture

The DL networks can be applied for image classification in many fields based on large datasets with around 60 million parameters and 650,000 neurons [47]. In practice, the network architecture can have five convolutional layers and three fully connected layers with different roles. There are two first convolution layers (standard layer and max-pooling layer), the 3rd and 4th convolution layers (directly connected), the last convolution layer (max-pooling layer), and the output layer (softmax layer).

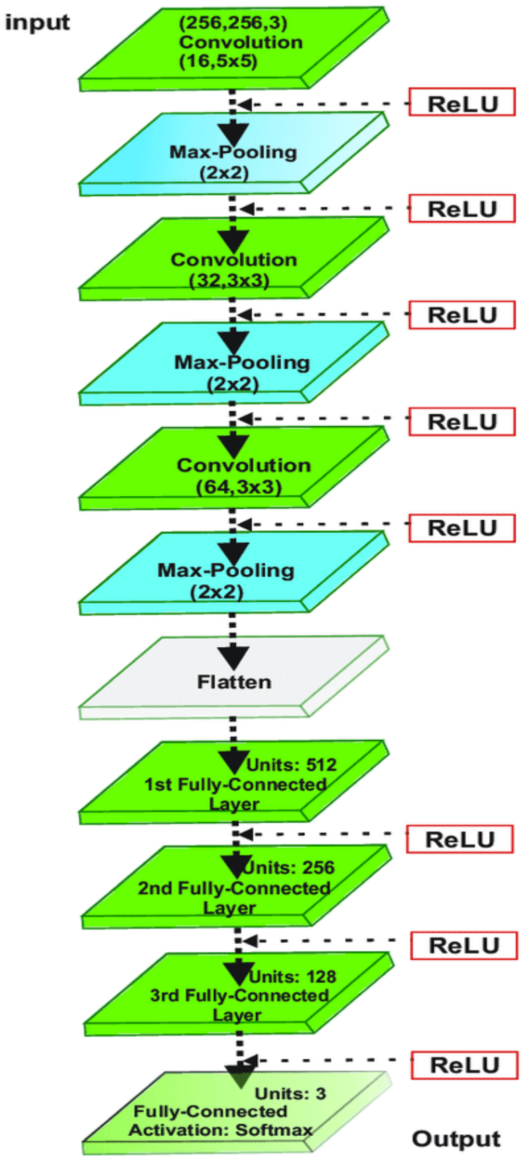


Figure 1.3: VGG-19 Architecture

Basically, VGG has an architecture of a CNN network, and VGG-19 is one of the VGG-based architectures [50]. The VGG-19 is a deep-learning neural network with 19 connection layers, including 16 convolution layers and 3 fully connected layers. The convolution layers will extract features of the input images, and the fully connected layers will classify the leaf images for those features. In addition, the max-pooling layers will reduce the features and avoid overfitting, as described in Figure 1.3.

The output of each convolutional layer is represented by the following expression:

$$C_j^l = \varphi\left(\sum_{i=1}^{M^{l-1}} C_i^{l-1} \times k_{ij}^l + b_j^{l-1}\right)$$

in which × is the convolutional function which describes the connection between the weights of the ith and jth features in the $(l-1)$th, lth layers, b_j is the bias value, and φ is the activation function.

Transfer Learning

Transfer learning is often used in DL networks from the trained object to re-train the other objects. There are four types of transfer learning: case-based, features-based, parameter-based, and relationship-based. Obviously, choosing the trained parameters for the best classification system is a big challenge. Here, a suitable network architecture needs to be addressed along with the network parameters, and these values need to be estimated for the new input data. Then, the new network needs to be fine-tuned to improve performance. In this paper, the parameter-based transfer learning method was applied for classifying tomato leaf diseases. In particular, the VGG-19 network will freeze the convolution layers and re-train the fully connected layers to enhance the classification. Furthermore, we also adjust the batch size, epoch, and learning rate to choose the best network.

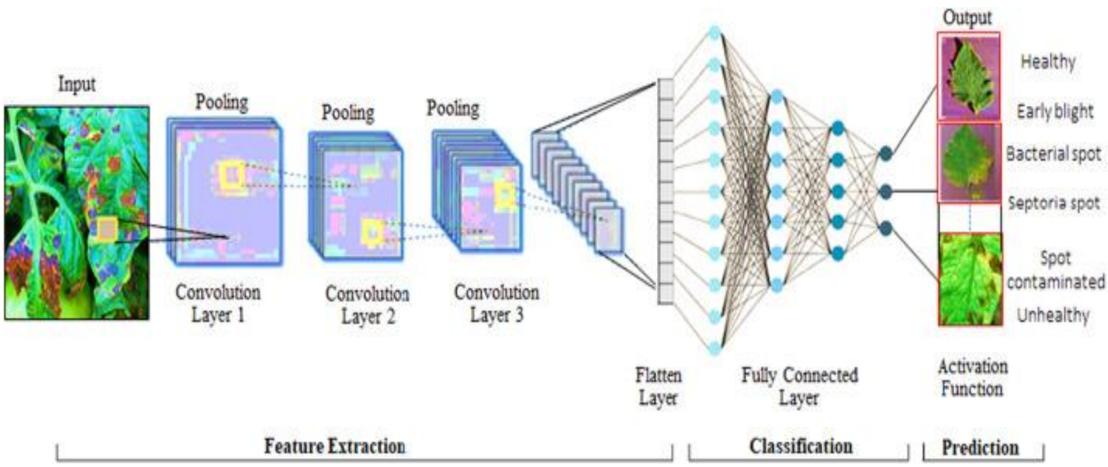


Figure 1.4:Transfer Learning

The VGG-19 is a deep and wide structure in which the number of computational parameters is well-optimized. In particular, the parameters were configured for training the network, including epochs (300), hidden layer active function (Tansig), output active function (Softmax), initial learning rate (0.00001), and batch size (60).
In this research, the division of 16,010 tomato leaf images (100%) in the Plant Village dataset is performed as follows: 80% of the image set for training and validation, and 20% of the image set for testing. In addition, the images for training and validation are divided into the training (80%) and the validation (20%).

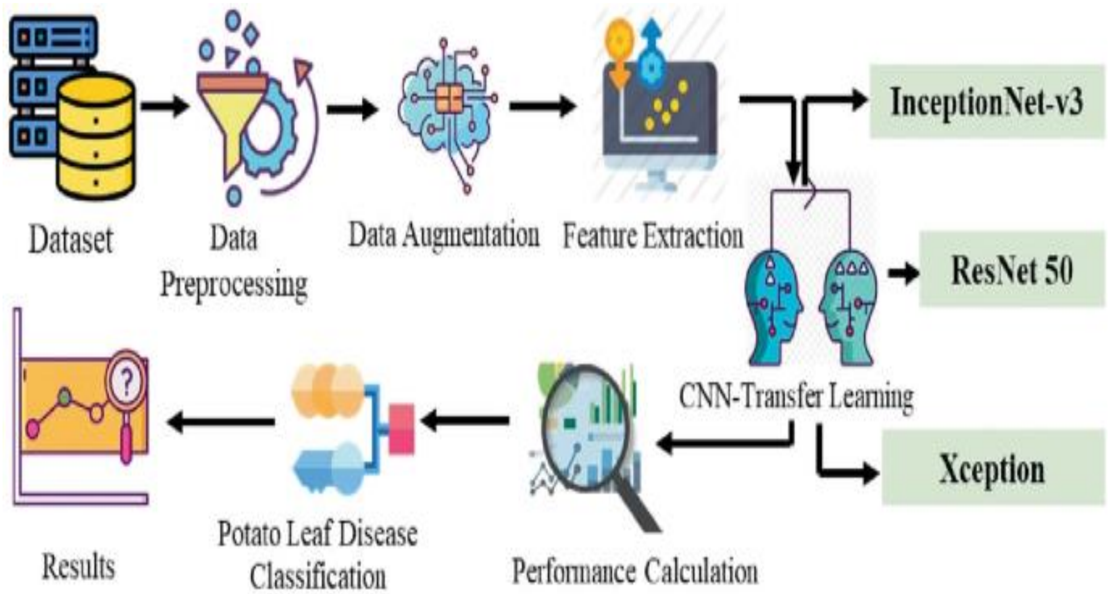


Figure 1.4.1 : Transfer Learning

ResNet-50

The ResNet-50 architecture is a variant of the Residual Network (ResNet) proposed by Kaiming He et al. in 2015. The model is characterized by its deep residual learning framework, which introduces skipconnections (also known as shortcut connections) to ease the training of very deep neural networks.

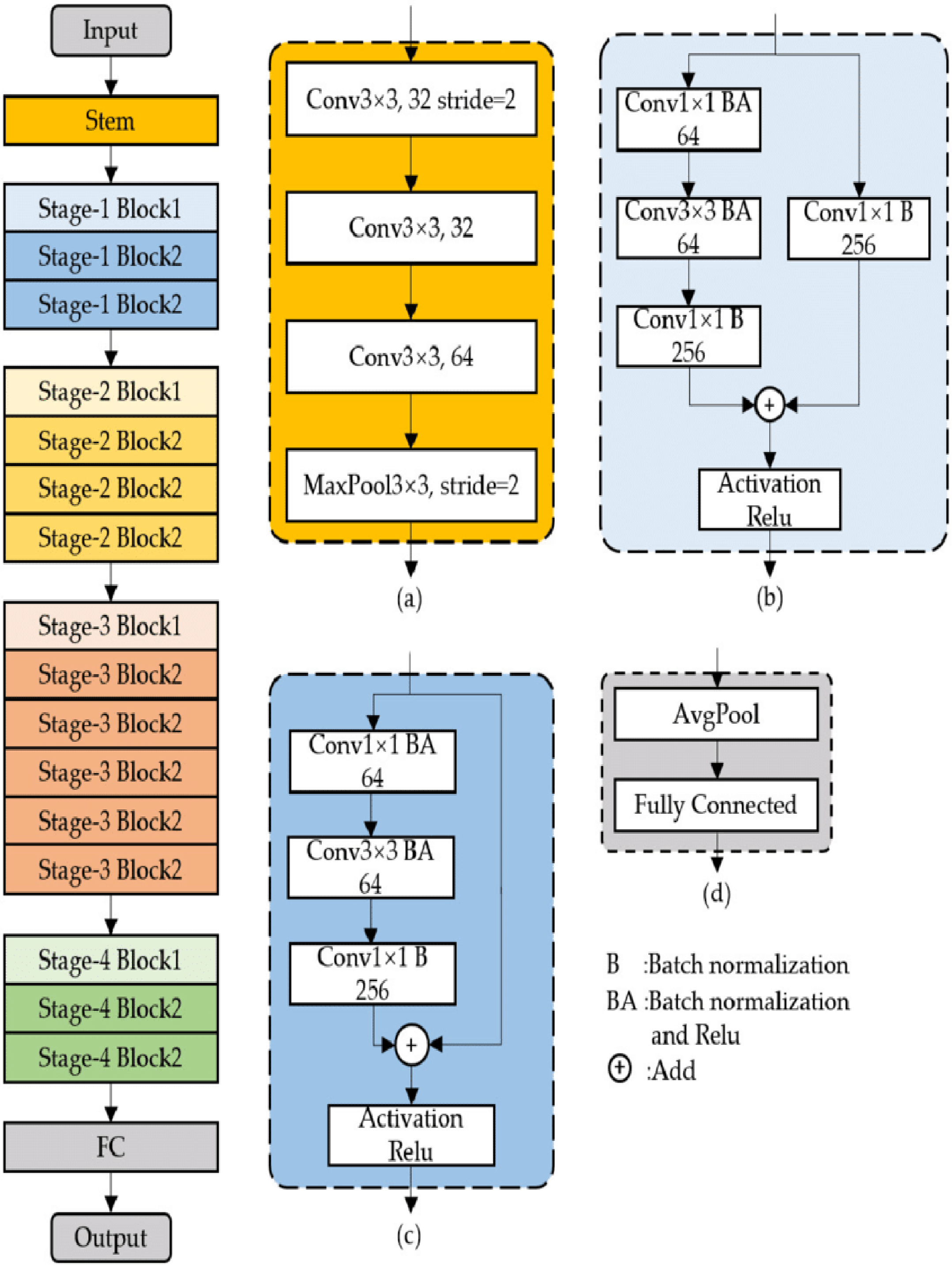


Figure 1.5 : ResNet-50

Skip Connections

ResNet-50 utilizes skip connections to create shortcuts between layers, enabling the network to learn residual functions instead of direct mappings. The shortcut connections skip one or more layers, directly connecting earlier layers to later ones. These shortcuts allow the model to preserve crucial information from the initial layers, mitigating the vanishing gradient problem during back propagation.

Residual Blocks:

The ResNet-50 architecture consists of multiple residual blocks. Each residual block comprises several convolutional layers and a skip connection. The most common residual block used in ResNet-50 is the bottleneck block, which reduces computational complexity while increasing the depth of the network.

Identity and Projection Shortcut

In ResNet-50, there are two types of skip connections: identity shortcuts and projection shortcuts. The identity shortcut preserves the input of the block, while the projection shortcut uses a 1x1 convolutional layer to project the input to match the dimensions of the output. The two shortcut types are employed based on the change in dimensions between inputand output feature maps.

Model Depth

ResNet-50 is a deep architecture comprising 50 layers, including 3 convolutional layers and 4 residual blocks. The model is pre-trained on massive datasets like ImageNet and can be fine-tuned for specific image recognition tasks with relatively fewer training data.

CNN Model

CNNs thinks about piece by piece of picture [1]. The pieces that CNN looks for are called highlights. It finding the harsh element matches in two pictures in similar positions, CNNs improve at seeing closeness than entire picture coordinating plans. Each component resembles a smaller than normal picture, a little two-dimensional cluster of qualities [1].

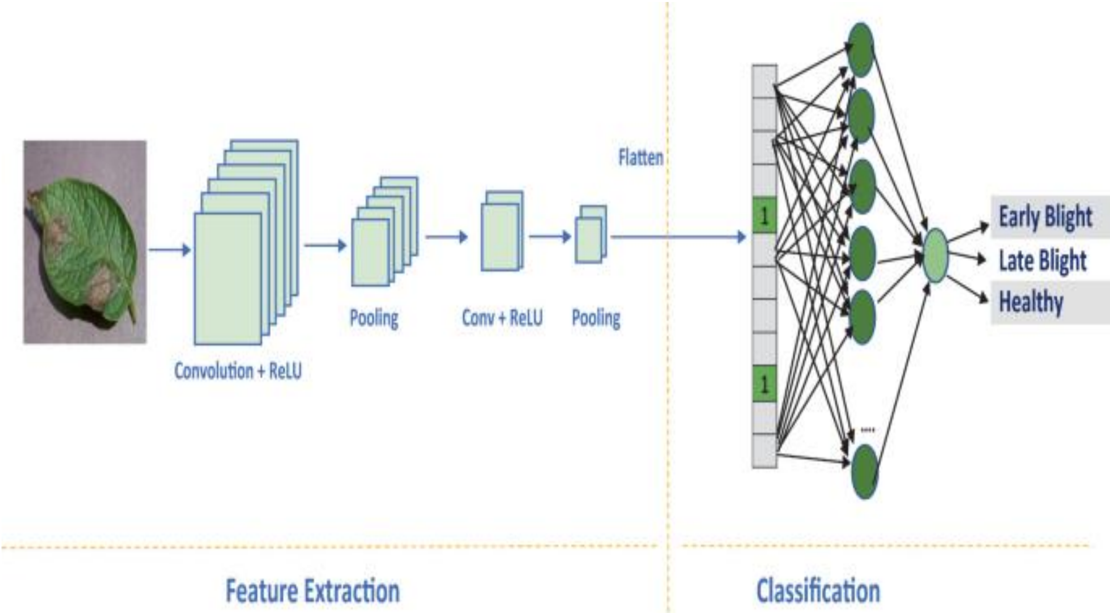


Figure1.6: CNN Architecture

We first create a sequel model of CNN with 7 levels. We used Adam Optimizer to measure performance error and tune cross entropy. We then use transfer learning to create the model. To do that we only use built in module keras, keras applications that provide pre-trained weights. We modified the Deep Learning model so that the pre-trained weights matched our desired output dimension by dropping the last few layers and adding few Junne lavens[1].

• Give input photograph into convolution layer

• Choose boundaries, apply channels with steps, cushioning if requires. Perform Convolution on the picture and apply ReLU enactment to the grid.

• Execute pooling to decrease Dimension size.

• Add as numerous convolutional layers until satisfied.

• Flatten the yield and feed into a completely associated layer.

• Output the class utilizing enactment and order pictures.

1.6 Design of Cold Storage Structure For Potatoes

Storage is the art of keeping the quality of agricultural materials and preventing them from deterioration for specific period of time, beyond their normal shelf life. Cold storage Control ripening retards aging, softening, texture and colour change, retards moisture loss, wilting, microbial activity, spoilage, sprouting and undesirable growth. Availability of proper cold storages are important for preserving perishable commodities like milk, meat, eggs, vegetables, fruits, ornamental flowers and other floricultural goods. These cold storages give perishable food items a longer shelf life by preventing them from rotting due to humidity, high temperature and microorganisms. This results in a decrease in loss due to spoilage. Potatoes are an important staple food crop and have a wide range of seasonal adaptability. It is a cool season crop and is moderately frost – tolerant. Temperature during the growing season has long been recognized as one of the most important factors influencing yield. Young plants grow best at a temperature of 24°C; later growth is favored at 18°C. Tuber production reaches a maximum at 20°C, decreases with rise in temperature, and at about 30°C tuber production stops entirely. Short days are beneficial for tuber production. Required temperature, relative humidity and storage period for early crop, seed potato and table potato are given in table-1

Table -1 storage conditions of potato

Fresh potato	Temperature	Storage period	Relative Humidity
Early Crop	$4\text{-}10^0$ C	0-3 months	95%
Seed Potato	3^0 C	5-10 months	90-95%
Table Potato	4^0 C	5-10 months	90-95%

Principles of Refrigeration The cold storage like every other refrigerating systems of the same magnitude employs the vapour compression method of mechanical refrigeration. Fig.1.7 presents the T-s diagram of the vapour compression cycle, while the Fig.2 illustrates the processes of the refrigeration employed in the cold room, respectively [2].

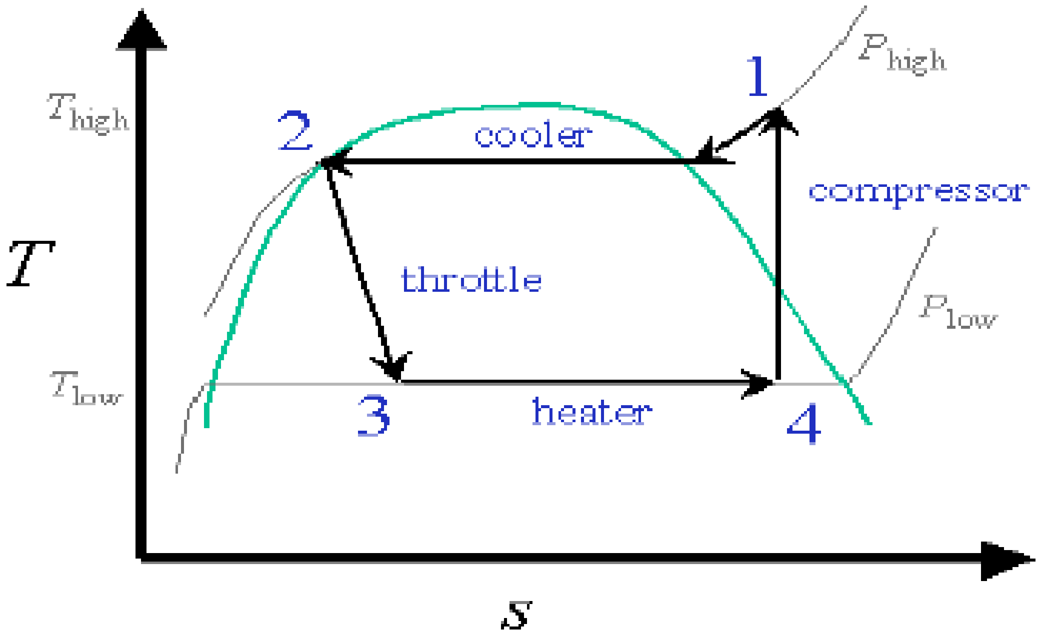


Fig.1.7: T-s diagram of the vapour compression cycle

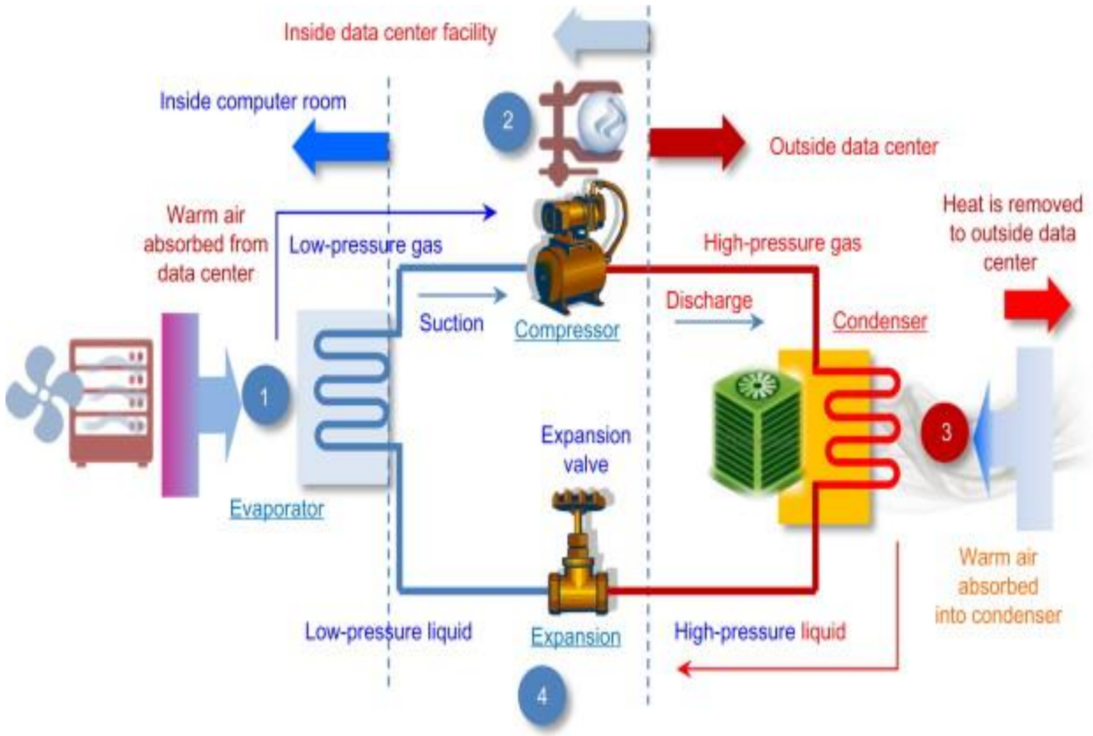


Fig.1.8. Processes of the refrigeration

CHAPTER 2

LITERATURE SURVEY

A literature survey or a literature review in a project report shows the various analyses and research made in the field of interest and the results already published, taking into account the various parameters of the project and the extent of the project. Literature survey is mainly carried out in order to analyze the background of the current project which helps to find out flaws in the existing system & guides on which unsolved problems we can work out. So, the following topics not only illustrate the background of the project but also uncover the problems and flaws which motivated to propose solutions and work on this project.

A literature survey is a text of a scholarly paper, which includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to a particular topic. Literature reviews use secondary sources, and do not report new or original experimental work. Most often associated with academic-oriented literature, such as a thesis, dissertation or a peer-reviewed journal article, a literature review usually precedes the methodology and results sectional though this is not always the case. Literature reviews are also common in are search proposal or prospectus (the document that is approved before a student formally begins a dissertation or thesis). Its main goals are to situate the current study within the body of literature and to provide context for the particular reader. Literature reviews are a basis for researching nearly every academic field. A literature survey includes the following:

- Existing theories about the topic which are accepted universally.
- Books written on the topic, both generic and specific.
- Research done in the field usually in the order of oldest to latest.
- Challenges being faced and on-going work, if available.

Literature survey describes about the existing work on the given project. It deals with the problem associated with the existing system and also gives user a clear knowledge on how to deal with the existing problems and how to provide solution to the existing problems..

Objectives of Literature Survey

• Learning the definitions of the concepts.

• Access to latest approaches, methods and theories.

• Discovering research topics based on the existing research.

• Concentrate on your own field of expertise– Even if another field uses the same words.

• It improves the qualityof the literature surveyto exclude sidetracks– Remember to explicate what is excluded.

Before building our application, the following system is taken into consideration:

2.1 Potato Leaf Diseases Detection Using Deep Learning

Author: Divyansh Tiwari, Mritunjay Ashish,Nitish Gangwar,Abhishek Sharma, Suhanshu Patel ,Dr. Suyash Bhardwaj.

Abstract: With the enhancement in agricultural technology and the use of artificial intelligence in diagnosing plant diseases, it becomes important to make pertinent research to sustainable agricultural development. Various diseases like early blight and late blight immensely influence the quality and quantity of the potatoes and manual interpretation of these leaf diseases is quite time-taking and cumbersome. As it requires tremendously a good level of expertise, efficient and automated detection of these diseases in the budding phase can assist in ameliorating the potato crop production. Previously, various models have been proposed to detect several plant diseases. In this paper, a model is presented that uses pre- trained models like VGG19 for fine-tuning (transfer learning) to extract the relevant features from the dataset. Then, with the help of multiple classifiers results were perceived among which logistic regression outperformed others by a substantial margin of classification accuracy obtaining 97.8% over the test dataset.

Methodology used: VGG19 for fine-tuning (transfer learning) with Logistic regression

Advantages:

Accuracy is higher than previous paper.

Limitations:

It supports only for the specific dataset.

It supports only to detect plant leaf disease.

2.2 Application of Transfer Learning to Detect Potato Disease from Leaf Image

Author: Farabee Islam,Md Nazmul Hoq,Professor Dr. Chowdhury Mofizur Rahman

Abstract: Potato is one of the most significant crops over the world. But production of potato is hampered due to some diseases which cause an increase of the cost as well as affect the life of the farmers. An automatic and early detection of these diseases will increase the production and help to digitize the system. Our main objective is to detect the potato diseases with a few leaf image data using advanced machine learning techniques. In this paper, we demonstrate that transfer learning technique could be used for early detection of potato diseases when it is difficult to collect thousands of new leaf images. Transfer learning uses already trained deep learning model's weight to solve new problem. The experiments included images of 152 healthy leaves, 1000 Late blight leaves, and 1000 early blight leaves. The program predicts with an accuracy of 99.43% in testing with 20% test data and 80% train data. We also compared sequential deep learning model with several pre-trained model applying transfer learning and found that transfer learning provided best result till date. Our output showed that transfer learning outperforms all existing works on potato disease detection.

Methodology used: transfer learning

Advantages:

Accuracy is higher than previous paper.

Limitations:

It supports only for the specific dataset.

It supports only to detect plant leaf disease.

2.3 Detection and differentiation between potato diseases using calibration models trained with non-imaging spectrometry data

Author: Damian Bienkowskia, Matt J. Aitkenheadb, Alison K. Leesc, Christopher Gallaghera, Roy Neilsona

Abstract: The proportion of light at wavelengths across the electromagnetic spectrum that is either absorbed, transmitted or reflected from a plant leaf is dependent on leaf structure, physiology and biochemistry. Since these elements are influenced by pests, pathogens and their associated induced diseases, the detection, differentiation and diagnosis of plant diseases is theoretically possible by non-destructive analysis of the light reflected from plant leaves. In this study the utility of analysis of light over the visible and near-infrared (400–1000 nm) portion of the spectrum to detect and distinguish between several economically important potato diseases, using either Partial Least Squares and Backpropagation Neural Network spectral calibration models was explored.

Models could detect and distinguish between diseases with obvious foliar symptoms (blackleg and late blight), even pre-symptomatically, correctly classifying spectra from greenhouse experiments with an accuracy of 84.6%. When these diseases were analyzed separately, models could distinguish between spectra from healthy and pre-symptomatic leaves, plus three classes of late blight lesion advancement with 92% accuracy. For blackleg, models distinguished between spectra from healthy, pre-symptomatic foliage and plants expressing blackleg symptoms with a 74.6% classification accuracy. However, models trained on spectra from whole-plant readings from field trials did not have this level of accuracy, with an r2 between target and model values of 0.66 for late blight, 0.31 for blackleg symptoms and 0.41 for healthy foliage. Regardless of greenhouse or field environment, models failed to detect or distinguish between diseases with subtle foliar impacts (black dot, powdery scab and Rhizoctonia diseases). While deployment of hand-held spectrometers for disease detection on a broad-acre scale is impractical, these findings could underpin methods to analyze hyperspectral imaging data with sub-plant resolution for incorporation into precision agriculture and Integrated Pest Management programmes for potato blackleg and late blight management.

Methodology used: Back Propagation Neural Network spectral calibration models.

Advantages:

It improves accuracy up to 75% in plant disease prediction.

Limitations:

It consumes more time to train the model.

It is not suitable to detect potato disease detection.

2.4 Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine

Author: Monzurul Islam, Anh Dinh, Khan Wahid, Pankaj Bhowmik

Abstract: Modern phenotyping and plant disease detection provide promising step towards food security and sustainable agriculture. In particular, imaging and computer vision-based phenotyping offers the ability to study quantitative plant physiology. On the contrary, manual interpretation requires tremendous amount of work, expertise in plant diseases, and also requires excessive processing time. In this work, we present an approach that integrates image processing and machine learning to allow diagnosing diseases from leaf images. This automated method classifies diseases (or absence thereof) on potato plants from a publicly available plant image database called `Plant Village'. Our segmentation approach and utilization of support vector

machine demonstrate disease classification over 300 images with an accuracy of 95%. Thus, the proposed approach presents a path toward automated plant diseases diagnosis on a massive scale.

Methodology used: SVM

Advantages:

Accuracy is higher than previous paper.

Limitations:

It supports for the specific dataset.

2.5 Detection of Potato Disease Using Image Segmentation and Machine Learning

Author: Md. Asif Iqbal and Kamrul Hasan Talukder

Abstract: Potato is one of the prominent food crops all over the world. In Bangladesh, potato cultivation has been getting remarkable popularity over the last decades. Many diseases affect the proper growth of potato plants. Noticeable diseases are seen in the leaf region of this plant. Two common and popular leaf diseases of the potato plants are Early Blight (EB) and Late Blight (LB). However, if these diseases were identified at an early stage it would be very helpful for better production of this crop. To solve this problem by detecting and analyzing these diseases image processing is the best option. This paper proposes an image processing and machine learning-based automatic system that will identify and classify potato leaf diseases. In this paper, image segmentation is done over 450 images of healthy and diseased potato leaf, which is taken from publicly available plant village database and seven classifier algorithms are used for recognition and classification of diseased and healthy leaves. Among them, The Random Forest classifier gives an accuracy of 97%. In this manner, our proposed approach leads to a path of automatic plant leaf disease detection.

Methodology Used: Random Forest Classifier.

Advantages:

Accuracy is higher than previous paper.

Limitations:

It supports only for the specific dataset.

It supports only to detect plant leaf disease.

2.6 Potato Leaf Diseases Detection and Classification System Mr

Author: Athanikar, Girish and Ms. Priti Badar.

Abstract: This report describes a neural network-based detection and classification of Potato leaf samples using Segmentation of K-Means Clustering. Algorithms are developed to acquire and process colour images of single leaf samples. Different leaves like healthy and diseased are considered for the study. The developed algorithms are used to extract over 24 (colour, texture and area) features. The texture features are extracted from the gray level cooccurrence matrix (GLCM).

A back Propagation Neural Network (BPNN)-based classifier isused to identify and classify the unknown leaf that is the leaf is healthy or diseased, if leaf is diseased, one then classify the disease by giving description (name, cause, pesticides). The colour, texture and area features are presented to the neural network for training purposes.

The trained network is then used to identify and classify the unknown leaf samples. The classification is carried out using different types of features sets, viz., colour, texture and area. Classification accuracies of over 92% are obtained for all the leaves samples (healthy and diseased) using all the three feature sets.

Methodology used: gray level co-occurrence matrix (GLCM). A back Propagation Neural Network (BPNN)

Advantages:

Multi features are extracted to improve accuracy.

Limitations:

It supports only for the specific dataset.

It supports only to detect plant leaf disease.

2.7 Detection and Classification of Leaf Disease Using Artificial Neural Network

Author: Malvika Ranjan, Manasi Rajiv Weginwar, NehaJoshi, A.B. Ingole

Abstract: Nowadays, herb plants are importance to medical field and can give benefit to human. In this research, Phyllanthus Elegans Wall (Asin-Asin Gajah) is used to analyse and to classify whether it is healthy or unhealthy leaf. This plant was chosen because its function can cure breast cancer. Therefore, there is a need for alternative cure for patient of breast cancer rather than use the technology such as Chemotherapy, surgery or use of medicine from hospital. The purpose of this research to identify the quality of leaf and using technology in agriculture field. The process to analysis the leaf quality start from image acquisition, image processing, and classification. For image processing method, the most important for this part is the segmentation using HSV to input RGB image for the color transformation structure. The analysis of leaf disease image is applied based on colour and shape. Finally, the classification method uses feed-forward Neural Network, which uses Back-propagation algorithm. The result shows comparison between Multi-layer Perceptron (MLP) and Radial Basis Function (RBF) and comparison between MLP and RBF shown in percentage of accuracy. MLP and RBF is algorithm for Neural Network. Conclusively, classifier of Neural Network shows better performance and more accuracy.

Methodology used: Multi-layer Perceptron (MLP) and Radial Basis Function (RBF)

Advantages:

It works for almost all types of plants.

Limitations:

Accuracy is less than 92%.

It consumes more time to train the model.

2.8 Content based paddy leaf disease recognition and remedy prediction using support vector machine

Author: F. T. Pinki, N. Khatun and S. M. M. Islam,

Abstract: Rice is one of the staple foods of the world. But the production of rice is hampered by various kind of paddy diseases. One of the main diseases of paddy is leaf disease. Generally, it is very time-consuming and laborious for farmers of remote areas to identify paddy leaf diseases due to unavailability of experts. Though experts are available in some areas, disease detection is performed by naked eye which causes inappropriate recognition sometimes. An automated system can minimize these problems. In this paper, an automated system is proposed for diagnosis three common paddy leaf diseases (Brown spot, Leaf blast, and Bacterial blight) and pesticides and/or fertilizers are advised according to the severity of the diseases. K-means clustering is used for separating affected part from paddy leaf image. Visual contents (color, texture, and shape) are used as features for classification of these diseases. The type of paddy leaf diseases is recognized by Support Vector Machine (SVM) classifier. After recognition, the predictive remedy is suggested that can help agriculture related people and organizations to take appropriate actions against these diseases.

Methodology used: SVM

Advantages:

It supports for multi class classifications.

It extracts the multi features.

Limitations:

Accuracy is less.

It is suitable for only paddy crop disease detection.

2.9 Application of support vector machine for detecting rice diseases using shape and colour texture features

Author: Yao Q, Guan Z, Zhou Y, Tang J, Hu Y, Yang B

Abstract: For detecting rice disease early and accurately, we presented an application of image processing techniques and Support Vector Machine (SVM) for detecting rice diseases. Rice disease spots were segmented and their shape and texture features were extracted. The SVM method was employed to classify rice bacterial leaf blight, rice sheath blight and rice blast. The results showed that SVM could effectively detect and classify these disease spots to an accuracy of 97.2%.

Methodology used: SVM

Advantages:

It supports for multi class classifications.

It extracts the multi features.

Limitations:

Accuracy is less.

It is suitable for only paddy crop disease detection.

2.10 Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN

Author: C. U. Kumari, S. Jeevan Prasad and G. Mounika,

Abstract: Agricultural productivity plays a major role in an Indian economy; therefore, the disease detection in the field of agriculture is important. Farmers struggle a lot for proper crop production due to multiple diseases affecting the plant so there is a need to detect the disease at initial stage. One major disease in the crop is leaf spot. The purpose of the proposed system is to identify the leaf spot using image processing techniques. In this research the disease detection is done in four stages, image acquisition, image segmentation, feature extraction and classification. For image segmentation is done with K-means clustering method and features are computed from disease affected cluster. Features such as Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation and Variance are extracted. The extracted features from disease cluster are given as classifier inputs to classify the disease. The classifier used in this paper is neural network (NN) classifier. It is observed that the accuracies for bacterial leaf spot and target spot of cotton leaf diseases as 90% and 80% respectively. For tomato leaf diseases- septoria leaf spot and leaf mold as 100%.

Methodology used: K-means and KNN.

Advantages:

It consumes less training time.

Limitations:

It supports only for leaf disease prediction.

CHAPTER 3

MODEL DESIGN

3.1 Activity Diagram:

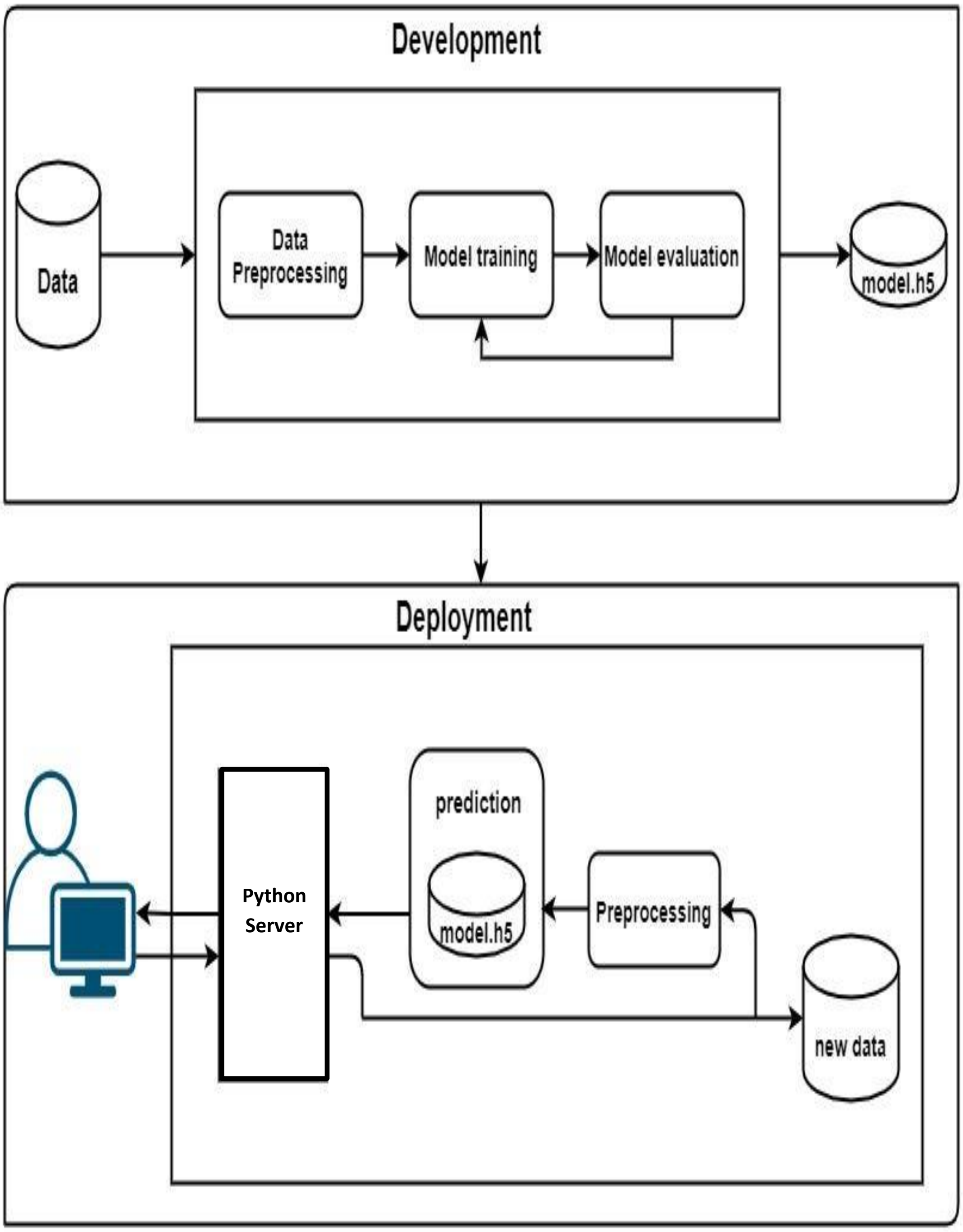


Figure 3.1: Activity diagram

3.2Use Case Diagram

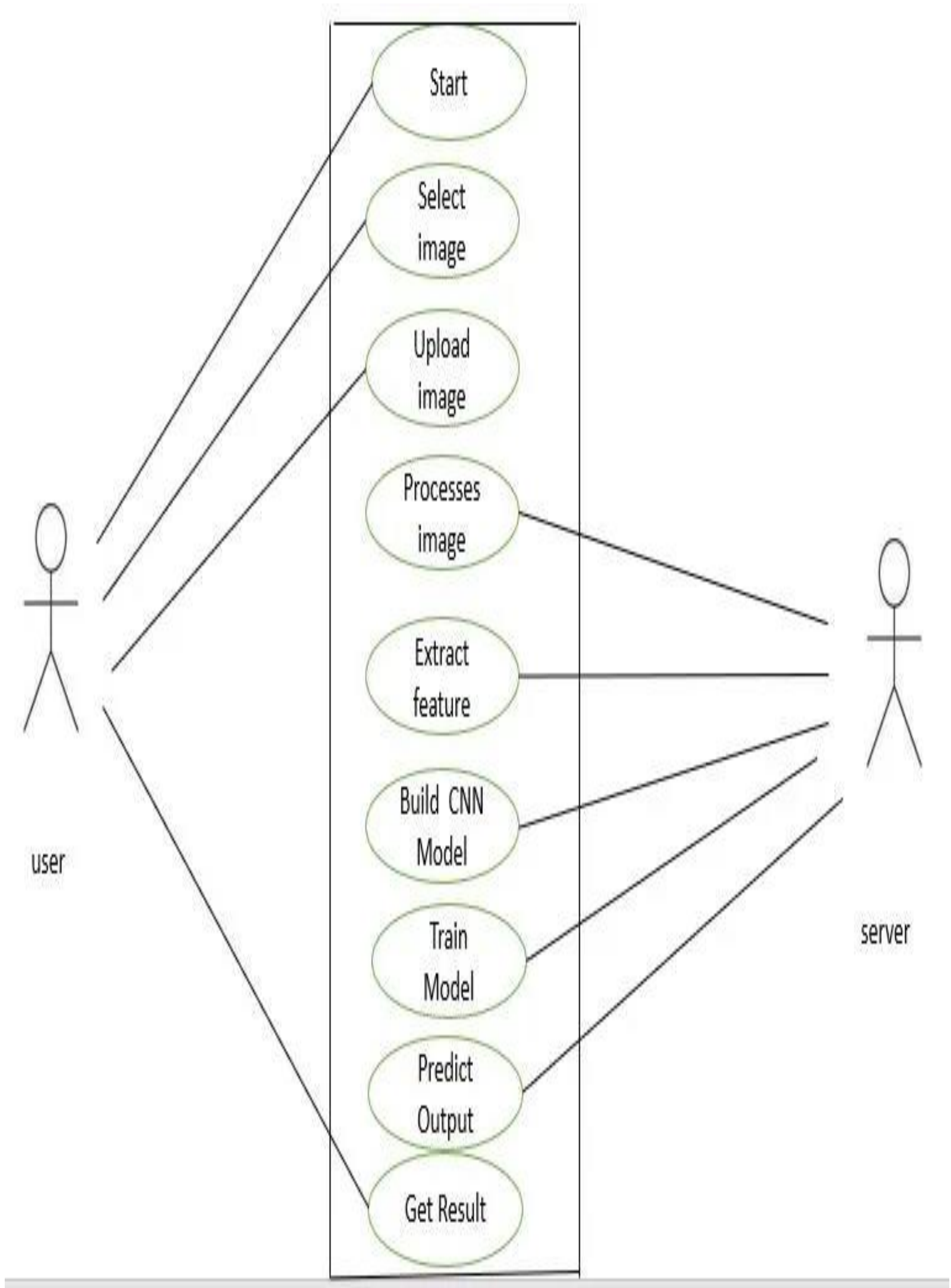


Figure 3.2: Use Case Diagram

3.3 Model Design

Model Design-Data Flow Diagram Level-0

Level: 0 describes the overall process of the project. We are using potato leaf disease image dataset as input. System will use VGG-16, VGG-19 ,RASNET50 , CNN algorithm to predict the potato disease or not.

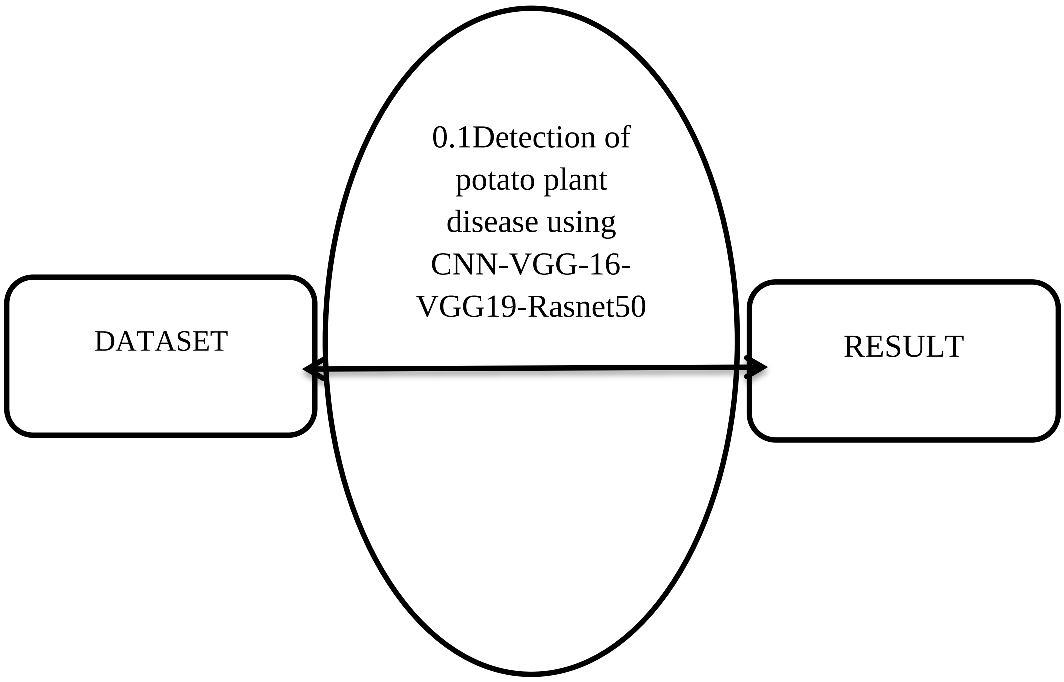


Figure 3.3: System design data flow diagram level-0

Model Design-Data Flow Diagram Level-1

Level: 1 describes the first step of the project. We are using image dataset as input. System will use Image generator to extract the image features and train the VGG-16 model and shows the performance graph as output.

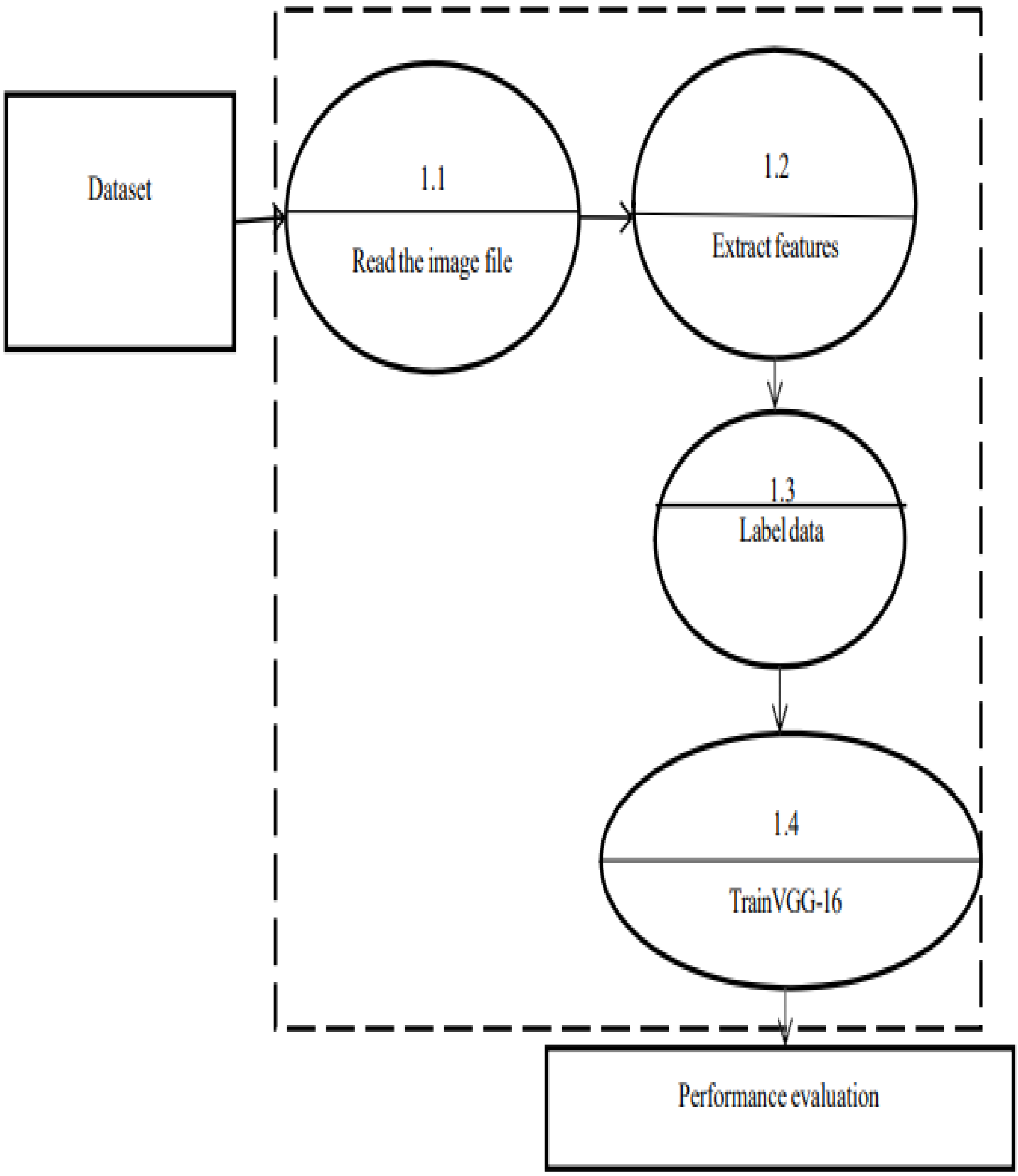


Figure 3.4: System design- data flow diagram level-1

System Design-Data Flow Diagram Level-2

Level: 2 describe the final step of the project. We are using trained model from level1 and image as input. System will use VGG-16 predicts the plant leaf is safe or unsafe.

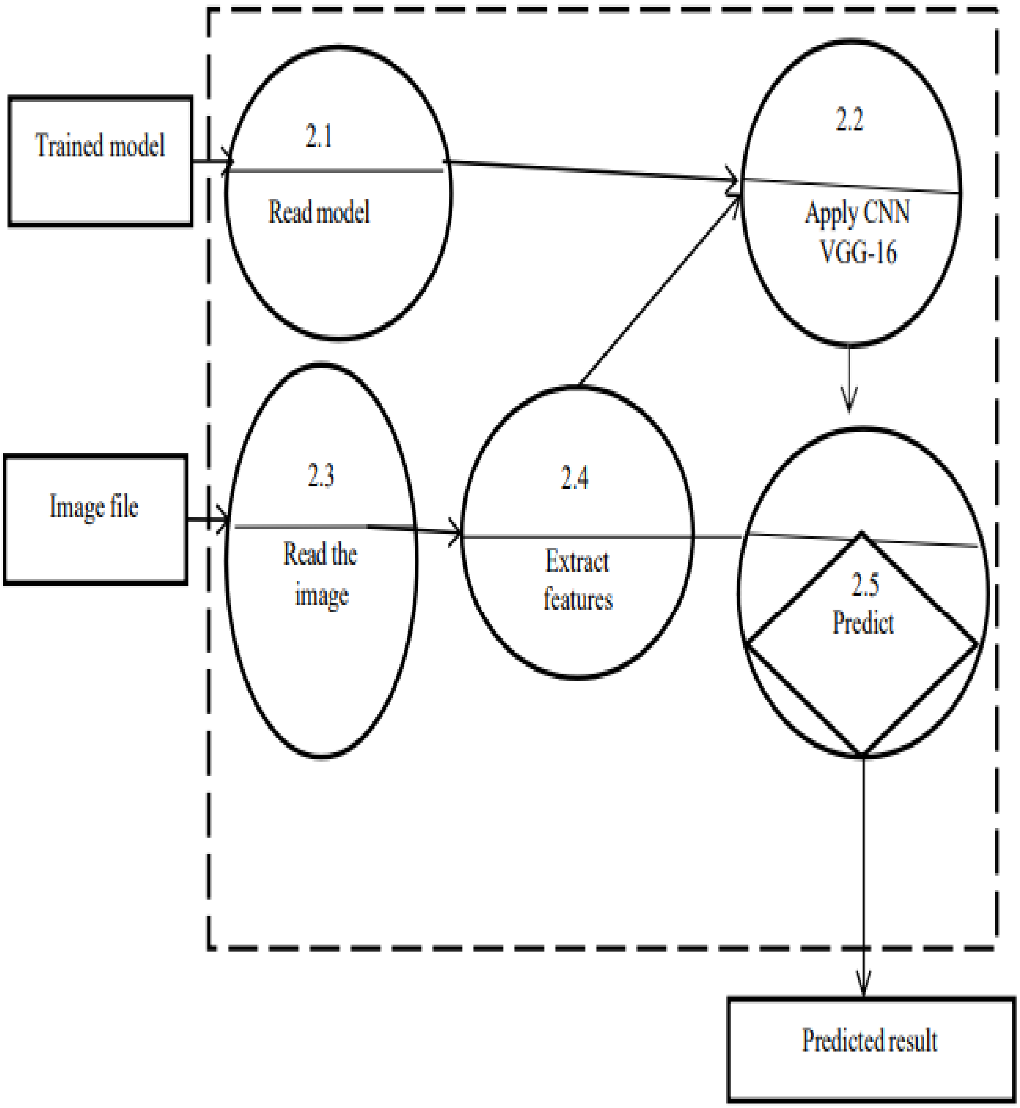


Figure 3.5: System Design Data flow diagram level-2

3.4 Heat load factors normally considered in a cold storage design

- Wall, floor and ceiling heat gains from solar radiation due to conduction
- Load due to ingression of air by frequent door openings and during fresh air charge.

Design of Cold Storage Structure For Thousand Tonne Potatoes

- Product load from incoming goods and heat of respiration from stored product
- Heat from workers working in the room
- Cooler fan load, light load, aging of equipment
- Miscellaneous loads, if any

3.2 Heat load calculations Cold storage for capacity 1000 tons requires room volume approximately 4000 m^3 because nearly 50-60 % of the total volume is utilized for storage purpose. For this purpose one room of size 18m X 15m X 10m (2700 m3) is considered.

3.2.1 Structural heat gain: It constitutes the heat transmission into the cold store through wall, ceiling and floor.

(a) Heat transmission through walls: - considering walls consisting of 1.5 cm thick plaster, 37 cm thick brick, 1.5 cm thick plaster, 10 cm thick thermocol, and 1.5 cm thick plaster, from outer to inner surfaces respectively.

$$Q = UA\,\Delta t$$

$$U = \frac{1}{\frac{1}{h_{out}} + \frac{x_1}{K_1} + \frac{x_2}{K_2} + \cdots + \frac{x_n}{K_n} + \frac{1}{h_{in}}} \qquad \text{———— Equation (1)}$$

$$U = \frac{1}{\frac{1}{4} + \frac{0.37}{0.25} + \frac{0.15 \times 3}{0.65} + \frac{0.1}{0.028} + \frac{1}{15}} = 0.183 \text{ kcal/m}^2\text{ h °C}$$

The storage temperature for potato is kept 5°C and outside temperature is taken 45°C. Heat flow per m2 /hour = U (tout – tin) = 0.183 (45-5) = 7.32 kcal/hour, Wall area = 660 m2 ,

Heat flow through walls = 660 X 7.32 = 4831.2 kcal/hour = 1.61 TR (b) Heat transmission through ceiling: - considering ceiling consisting of 3mm thick asbestos sheet and 10 cm thick thermocol. From equation (1)-

$$U = \frac{1}{\frac{1}{4} + \frac{0.1}{0.028} + \frac{0.003}{2.7} + \frac{1}{15}} = 0.25\ \text{kcal/m}^2\text{hr°C}$$

Heat flow per m2 /hour = 10 kcal/hr, wall area = 270 m2, Heat flow through walls = 0.9 TR (c) Heat transmission through floor: - Considering floor consisting of 6cm thick sand, 10cm thick rubble filling, 8cm thick cement concrete, 10 cm thick thermocol and 1 cm thick cement plaster. From equation (1)

$$U = \frac{1}{\frac{1}{4} + \frac{0.06}{0.6} + \frac{0.1}{9.2} + \frac{0.08}{0.7} + \frac{0.1}{0.028} + \frac{0.01}{0.65} + \frac{1}{15}} = 0.25\ \text{kcal/m}^2\text{h°C}$$

Heat flow per m2 /hour = 9.6 kcal/hour, Heat flow through walls = 2592 kcal/hour = 0.864 TR

(d) Heat transmission through door: - Door is made up of M.S. sheet with thermocol insulation are taken. Size of the door is 1.25m X 2.5 m. Average air changes per hour for 2700 m3 storage room due to door opening and infiltration is 0.06.

Heat gain, Q = room volume × air changes per hour × air density × enthalpy change

= 2700 × 0.06 × 0.85 × (40-3) = 5094.9 kcal/hr = 1.7 TR

.2 Equipment load :- (From lighting, evaporators etc.) Here it is assumed that 10 KW is required for this purpose so the equipment loads= 10×860/3000 =2.86 TR 3.2.3 Cooling down to freezing point: - Here cp above freezing point for potato is taken 0.82. Two months are taken for harvesting and during this period 1000 Tonne potatoes are to be stored, hence daily loading rate will be 20 Tons / day. It is assumed that potato is cooled for 24 hours

$$\text{Initial cooling} = \frac{20 \times 1000 \times 0.82(45 - 5)}{24 \times 3000} = 9.11\text{TR}$$

Heat evolved in storage: - The heat evolved in storage of potatoes at 5°C = 450 kcal/ton/day.

$$\text{Heat evolved} = \frac{1000 \times 450}{24 \times 3000} = 6.25\text{TR}$$

Heat of respiration: - Assuming respiration rate 10 KW/ ton (taking average value).

Heat of respiration= 1000×10×860/3000=2.86T

Human occupancy: - Assuming number of occupants working in cold storage be 3 and working for 10 hours in a day. The amount of heat dissipated by them is 430 kcal/hour (each). Hence heat load due to human occupancy is given by-

$$= \frac{3 \times 430 \times 10}{24} = 537.5 \text{ kcal/hr} = 0.1719\text{TR}$$

Hence, Total TR =5.074 + 2.86 + 9.11 + 6.25 + 2.86 + 0.1719 = 26.3259 TR. Assuming 10-15 % more of calculated TR to be the heat load. Therefore, Total TR = 30 TR.

CHAPTER 4

IMPLEMENTATION

- Data Collection
- Pre-processing
- Building and Training Model
- Classification of Disease

Implementation-Data Collection

We collected this information from kaggle website. We were able to collect data on about 3 types of diseases of potato leaves.

- Phytopthora Infestans
- Alternaria Solani
- Healthy potato leaves
- Virus
- Insect

Implementation-Preprocessing

In this project we have to take four types of image processing steps to normalize the image, change the color of the image, and identify the properties, Image processing such as filtering and transformation of the image. We have used Python's Opencv Library for this purpose. The features of the OpenCV library are:

- Read & write images
- Capture and save the images
- Image-processing such as filtering and transformation
- Detection the feature image or picture object detection

The picture document is perused with the OpenCV work the request for colors is BGR. Then again, in Pillow, the request for colors is thought to be RGB.

Implementation-Building and Training

CNNs thinks about piece by piece of picture. The pieces that CNN looks for are called highlights. It finding the harsh element matches in two pictures in similar positions, CNNs improve at seeing closeness than entire picture coordinating plans. Each component resembles a smaller than normal picture, a little two-dimensional cluster of qualities.

- Give input photograph into convolution layer Choose boundaries,
- apply channels with steps, cushioning if requires.
- Perform Convolution on the picture and apply ReLU enactment to the grid.
- Execute pooling to decrease Dimension size. Add as numerous convolutional layers until satisfied.
- Flatten the yield and feed into a completely associated layer. Output the class utilizing enactment and order pictures.

Classification of Disease

By applying the CNN-VGG-16 model our system will automatically classify the potato disease in the input image.

CHAPTER 5

TESTING

INTRODUCTION

This chapter gives the outline of all testing methods that are carried out to get a bug free system. Quality can be achieved by testing the product using different techniques at different phases of the project development. The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components subassemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement

1. Sample Collection: The first step in disease classification testing is to collect samples of potato plants showing symptoms of disease. These samples may include leaves, stems, or tubers exhibiting characteristic signs such as discoloration, lesions, or deformities.

2. Visual Inspection: Upon sample collection, trained experts visually inspect the samples to identify any visible symptoms associated with common potato diseases. These may include early blight, late blight, potato virus Y, bacterial wilt, and others. Visual inspection serves as the initial screening method for disease identification.

3. Laboratory Analysis: In cases where visual inspection alone is insufficient for accurate disease diagnosis, laboratory analysis may be conducted. This involves various techniques such as microscopy, serological tests, and molecular assays (e.g., PCR) to detect the presence of specific pathogens or disease-causing agents in the plant samples.

4. Image Processing: With advancements in technology, image processing techniques are increasingly being employed for disease classification testing. High-resolution images of diseased potato plants are captured using digital cameras or smartphone cameras. These images are then analyzed using computer vision algorithms to detect and classify diseases based on visual patterns and characteristics.

5. Machine Learning Models: Machine learning algorithms, particularly supervised learning techniques such as convolutional neural networks (CNNs), are trained using annotated image datasets to recognize patterns associated with different potato diseases. These models can then automatically classify new images of potato plants into relevant disease categories with a high degree of accuracy.

6. Validation and Evaluation: The performance of disease classification models is validated and evaluated using independent datasets or through cross-validation techniques. Metrics such as accuracy, precision, recall, and F1 score are calculated to assess the model's effectiveness in correctly identifying and classifying potato diseases.

7. Deployment and Integration: Once validated, the disease classification models can be deployed as part of decision support systems or mobile applications for real-time disease monitoring and management in potato fields. Farmers can use these tools to make informed decisions regarding disease control measures, crop rotation strategies, and pesticide applications.

5.1 METHODS OF TESTING

5.1.1 UNIT TESTING

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

Test strategy and approach

Field testing will be performed manually and functional tests will be written in detail.

Test objectives

- All field entries must work properly.
- Pages must be activated from the identified link.
- The entry screen, messages and responses must not be delayed.

Features to be tested

- Verify that the entries are of the correct format
- No duplicate entries should be allowed
- All links should take the user to the correct page

5.1.2 SYSTEM TESTING

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration-oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

5.1.3 FUNCTIONAL TESTING

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input: identified classes of valid input must be accepted.

Invalid Input: identified classes of invalid input must be rejected.

Functions: identified functions must be exercised.

Output: identified classes of application outputs must be exercised.

Systems/Procedures: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify

Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined

5.1.4 INTEGRATION TESTING

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

5.1.5 USER ACCEPTANCE TESTING

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

5.2 Test Cases: All the test cases mentioned above passed successfully. No defects encountered

Test Cases

Table 5.2.1: Unit Testing Case 1

Test Case	UTC01
Test Name	User input format
Test Description	To test user input format
Input	Potato leaf images
Expected Output	The file should be read by the program and display the images.
Actual Output	The file is read and display contents accordingly

Test Result	Success

Table 5.2.2: Unit Testing Case 2

Test Case	UTC02
Test Name	User input format
Test Description	To test user input format
Input	Images as null
Expected Output	Show alert messages select images
Actual Output	Show alert messages select images
Test Result	Success

Table 5.2.3: Unit Testing Case 3

Test Case	UTC03
Test Name	Pre-process
Test Description	To test whether resize frame size
Input	Images
Expected Output	It should resize images

Actual Output	Resized images
Test Result	Success

Table 5.2.4: Unit Testing Case 4

Test Case	UTC04
Test Name	Feature extraction
Test Description	To test whether it is extracting features from images
Input	Resized images
Expected Output	It extract feature and pass toVGG16 model
Actual Output	Resized images
Test Result	Success

Table 5.2.5: Unit Testing Case 5

Test Case	UTC05
Test Name	Test case to determine the potato leaf disease
Test Description	To test whether a given statistical model predicts the disease name of given user input
Input	The algorithm should predict the disease name as per

	historical Data collected
Expected Output	The predicted value by algorithm is closer to the specified value in the historical data
Actual Output	Resized images
Test Result	Success

Table 5.2.6: Unit Testing Case 6

Test Case	UTC06
Test Name	Test case for importing valid python libraries
Test Description	To test whether an algorithm to implement congestion nodes. works without sklearn and keras models
Input	Import all valid libraries sklearn and keras libraries
Expected Output	An error should be thrown specifying –error importing libraries sklearn and keras libraries
Actual Output	An error is thrown
Test Result	Success

CHAPTER 6

PERFORMANCE ANALYSIS/RESULT

VGG16

In this study, we segmented the input images using K-means clustering. We employed four classification methods, including VGG16, VGG19, ResNet50, and BASIC CNN to predict the classes of the leaf. On the training set, each model was trained for 30 epochs. Fig.6.1 shows the accuracy and loss for VGG16 as the best model, For various choices of K values, we also computed performance metrics like accuracy, precision, recall, F1-score, and confusion matrix.

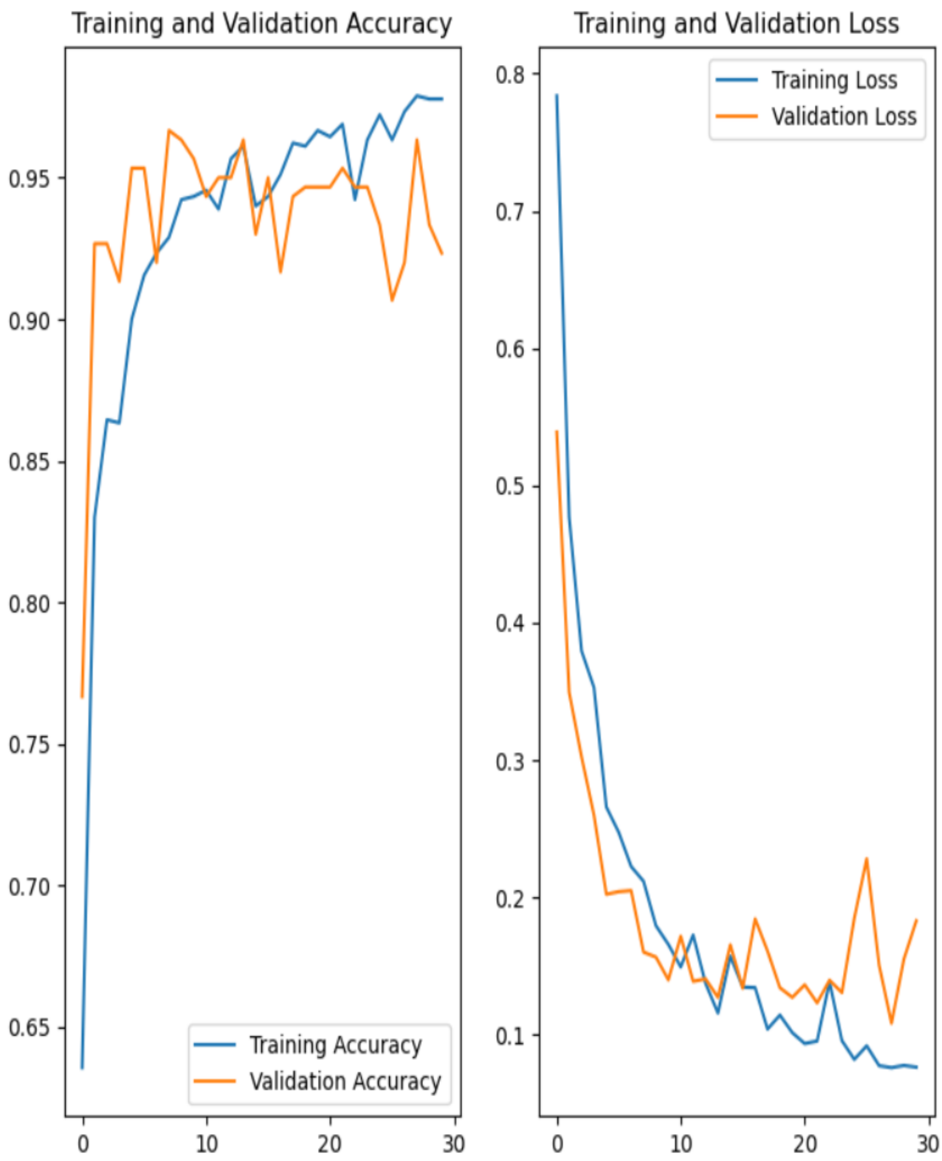


Figure 6.1: VGG16 Accuracy Visualization

The Performance of VGG16 model in the form of precision recall and f1-score.

```
Precision:  0.10448979591836734
F1 Score:  0.15753846153846152
Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        39
           1       0.00      0.00      0.00        29
           2       0.33      1.00      0.49        32

    accuracy                           0.32       100
   macro avg       0.11      0.33      0.16       100
weighted avg       0.10      0.32      0.16       100
The confusion matrix precision score and f1-score
Confusion Matrix:
 [[ 0  2 37]
 [ 0  0 29]
 [ 0  0 32]]
```

The VGG-16 model to achieve an impressive accuracy of 96%. The model effectively distinguishes between various diseases affecting potatoes, aiding in early detection and management. This breakthrough in agricultural technology offers farmers a powerful tool to combat crop diseases, thereby potentially increasing yields and reducing losses. By leveraging deep learning techniques, the project contributes to sustainable agriculture practices by enabling proactive disease management strategies. The high accuracy rate demonstrates the efficacy and reliability of the VGG-16 model in accurately classifying potato diseases, laying the groundwork for further advancements in crop disease detection and prevention.

VGG19

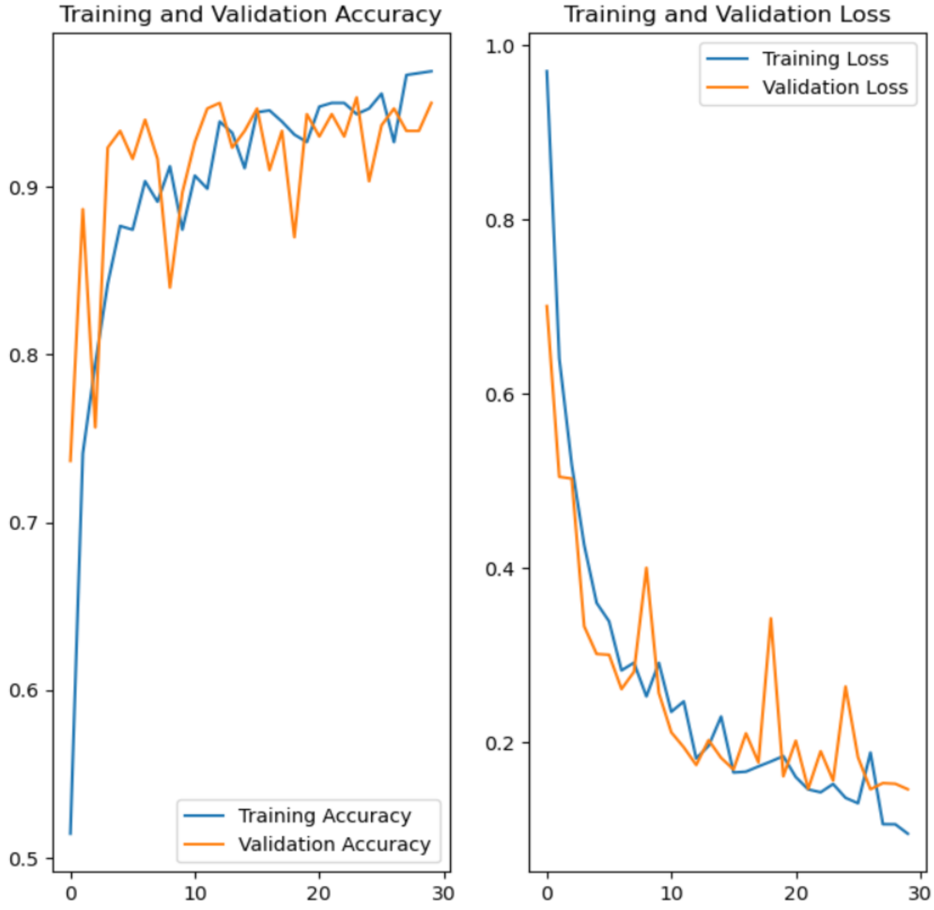


Figure 6.2. VGG19 Accuracy Visualization

The Performance of VGG19 model in the form of precision recall and f1-score.

```
Precision:  0.1024
F1 Score:  0.15515151515151515

       precision    recall  f1-score   support

           0       0.00      0.00      0.00        29
           1       0.00      0.00      0.00        39
           2       0.32      1.00      0.48        32

    accuracy                           0.32       100
   macro avg       0.11      0.33      0.16       100
weighted avg       0.10      0.32      0.16       100
```

The confusion matrix precision score and f1-score

```
Confusion Matrix:
 [[ 0  0 29]
 [ 0  0 39]
 [ 0  0 32]]
```

The VGG19 model was deployed, achieving a commendable accuracy of 94%. This variant of the VGG architecture demonstrated robust performance in distinguishing between different potato diseases, showcasing its versatility in agricultural applications. The model's ability to accurately classify diseases offers farmers valuable insights into crop health, empowering them to take timely action to mitigate potential losses. Despite a slightly lower accuracy compared to VGG16, the VGG19 model still proves to be a reliable tool for disease detection in potatoes, highlighting the importance of exploring various deep learning architectures for agricultural advancements.

ResNet50

Figure 6.3. Resnet50 Accuracy Visualization

The Performance of RESNET50 model in the form of precision recall and f1-score.

```
Precision:  0.10890000000000001
F1 Score:  0.1637593984962406
Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        35
           1       0.33      1.00      0.50        33
           2       0.00      0.00      0.00        32

    accuracy                           0.33       100
   macro avg       0.11      0.33      0.17       100
weighted avg       0.11      0.33      0.16       100
```

The confusion matrix precision score and f1-score

```
Confusion Matrix:
 [[ 0 35  0]
 [ 0 33  0]
 [ 0 32  0]]
```

The resnet50 model was utilized, achieving an accuracy of 54%. While this accuracy is lower compared to the previous models, it still presents valuable insights into disease detection in potatoes. The resnet50 model's performance underscores the importance of exploring different deep learning architectures to address complex agricultural challenges. Despite the lower accuracy rate, the model offers a foundation for further refinement and optimization, potentially improving its effectiveness in identifying potato diseases. This highlights the iterative nature of deep learning research and the continuous quest for innovative solutions in agriculture to enhance crop health and yield.

BASIC CNN

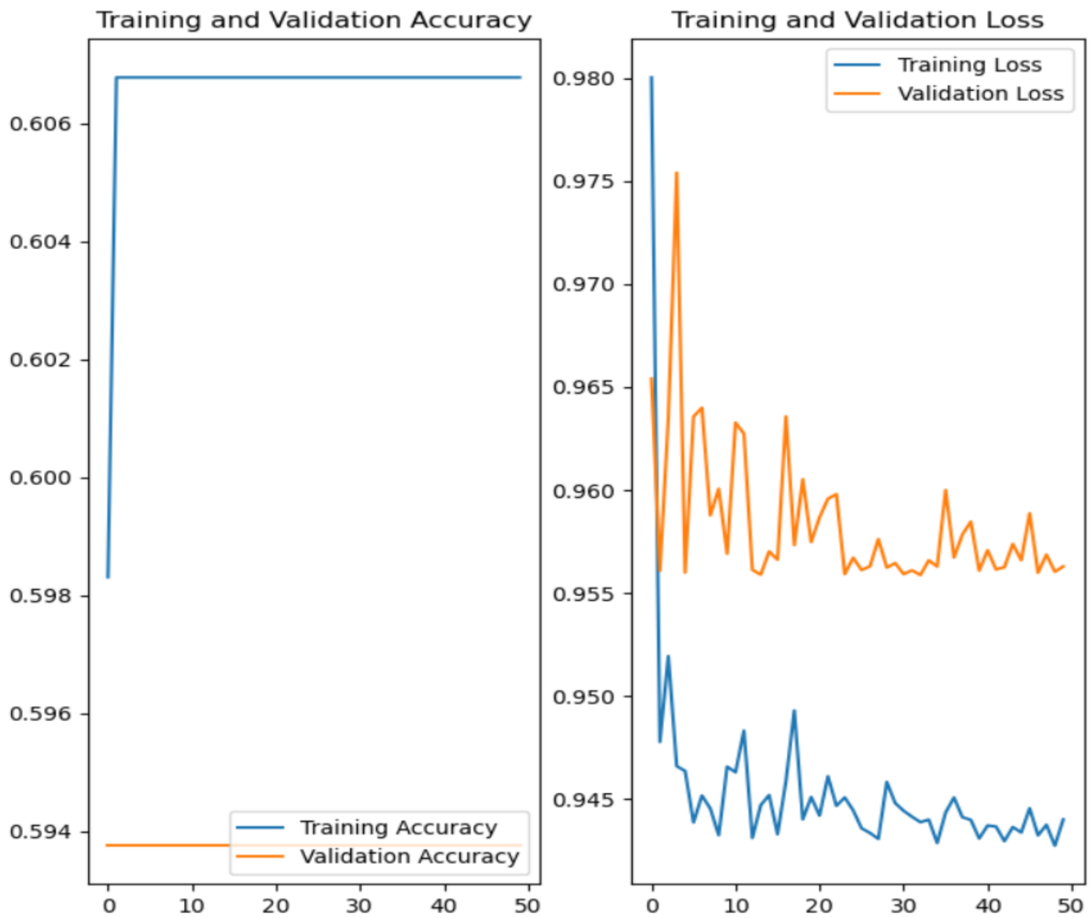


Fig 6.4. Basic CNN Accuracy Visualization

The Performance of RESNET50 model in the form of precision recall and f1-score.

```
Precision:  0.10890000000000001
F1 Score:  0.1637593984962406
Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        35
           1       0.33      1.00      0.50        33
           2       0.00      0.00      0.00        32

    accuracy                           0.33       100
   macro avg       0.11      0.33      0.17       100
weighted avg       0.11      0.33      0.16       100
```

The confusion matrix precision score and f1-score

```
Confusion Matrix:
 [[ 0 35  0]
 [ 0 33  0]
 [ 0 32  0]]
```

A basic Convolutional Neural Network (CNN) model was employed, achieving an accuracy of 62%. Despite its simplicity compared to more complex architectures like VGG or resnet, the basic CNN still demonstrates promise in classifying potato diseases. While its accuracy may be lower than more sophisticated models, it provides a cost-effective and accessible option for farmers seeking to implement AI-driven disease detection solutions. The performance of the basic CNN underscores the potential for leveraging simpler models in agricultural contexts, where computational resources or expertise may be limited. This highlights the versatility of deep learning techniques in addressing real-world agricultural challenges.

Ai-powered potato disease detection

Aimed to leverage various deep learning models to classify diseases affecting potatoes, contributing to early detection and management strategies for farmers. Four different models were employed: vgg16, vgg19, resnet50, and a basic convolutional neural network (cnn). Each model exhibited varying degrees of accuracy, shedding light on their effectiveness in addressing agricultural challenges.

The vgg16 model, with an impressive accuracy of 96%, emerged as a standout performer in the project. Its high accuracy demonstrates its efficacy in accurately identifying and classifying potato diseases, offering farmers valuable insights for proactive disease management. The vgg19 model, while slightly less accurate at 94%, still showcased robust performance, highlighting the versatility of the vgg architecture in agricultural applications.

In contrast, the resnet50 model achieved an accuracy of 54%, significantly lower than the vgg models. Despite this, its performance provides valuable insights into disease detection in potatoes, emphasizing the importance of exploring different deep learning architectures. Additionally, the basic cnn model, with an accuracy of 62%, demonstrated potential as a cost-effective solution for farmers, despite its simplicity compared to more complex models.

Overall, the project underscores the significance of deep learning in agriculture, particularly in crop disease detection and management. By harnessing advanced neural network architectures, farmers can make informed decisions to protect their crops and optimize yields. The varying accuracies of the models highlight the iterative nature of research, with each model contributing valuable insights and paving the way for further advancements.

The success of the vgg16 and vgg19 models showcases the effectiveness of the vgg architecture in classifying potato diseases. Their high accuracies validate the suitability of these models for real-world agricultural applications, offering farmers reliable tools for disease detection. Furthermore, their performance underscores the potential for deep learning to revolutionize agricultural practices, enabling more efficient and sustainable crop management strategies.

While the resnet50 model exhibited lower accuracy compared to the vgg models, its results still provide valuable contributions to the project. The insights gained from its performance can inform future research directions, potentially leading to improvements in disease detection algorithms for potatoes and other crops. Additionally, the basic cnn model's modest accuracy highlights the importance of considering simpler architectures, especially in resource-constrained environments.

Beyond their individual performances, the collective results of the four models offer a comprehensive overview of deep learning's impact on potato disease classification.

Each model contributes unique insights and challenges, driving innovation and progress in agricultural technology. By exploring a diverse range of architectures, researchers can better understand the strengths and limitations of different approaches, ultimately leading to more effective solutions for farmers worldwide.

Intelligent storage sorting system

Integrates advanced technologies to optimize potato storage conditions. Employing a multifaceted approach, the system meticulously controls temperature, humidity, ventilation, and gas composition within storage facilities to preserve potato quality and minimize spoilage.

Temperature regulation plays a crucial role in maintaining potato freshness. The system continuously monitors and adjusts temperatures to prevent extremes that could lead to sprouting, rotting, or other forms of deterioration. By maintaining an optimal temperature range, typically between 4 to 10 degrees Celsius, the system slows down enzymatic activity and inhibits the growth of pathogens, thereby extending the shelf life of stored potatoes.

Humidity management is equally vital in preserving potato quality. The system carefully controls humidity levels to prevent excess moisture buildup, which can lead to rotting and mold growth. By maintaining appropriate humidity levels, typically between 85% to 95%, the system ensures that potatoes retain their firmness and texture while minimizing the risk of spoilage.

Ventilation within the storage facility helps to regulate air circulation, preventing the buildup of harmful gases and maintaining uniform storage conditions throughout the facility. Proper ventilation ensures that all potatoes receive adequate airflow, reducing the likelihood of localized hotspots or areas of excess moisture.

Gas composition monitoring involves controlling oxygen and carbon dioxide levels within the storage environment. By adjusting gas concentrations, the system can slow down the respiration rate of potatoes, effectively delaying the onset of sprouting and senescence. This meticulous control of gas composition helps to extend the shelf life of stored potatoes and maintain their quality during storage.

By integrating these temperature, humidity, ventilation, and gas composition monitoring technologies, the intelligent storage system ensures that potatoes remain fresh, healthy, and market-ready for an extended period. This not only minimizes waste but also maximizes profitability for farmers and suppliers by preserving the quality of their produce.

CHAPTER 7

FEASIBILITY STUDY

Depending on the results of the initial investigation the survey is now expanded to a more detailed feasibility study. FEASIBILTY STUDY is a test of system proposal according to its workability, impact of the organization, ability to meet needs and effective use of the resources. The steps involved in the feasibility analysis are:

- ✓ Form a project team and appoint a project leader.
- ✓ Enumerate potential proposed system.
- ✓ Define and identify characteristics of proposed system.
- ✓ Determine and evaluate performance and cost effective of each proposed system.
- ✓ Weight system performance and cost data.
- ✓ Select the best proposed system.
- ✓ Prepare and report final project directive to management.

Three key considerations involved in the feasibility analysis are:

- ✓ ECONOMICAL FEASIBILITY
- ✓ TECHNICAL FEASIBILITY
- ✓ SOCIAL FEASIBILITY

7.1 ECONOMICAL FEASIBILITY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus, the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

7.2 TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

7.3 SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

CHAPTER 8

CONCLUSION & FUTURE ENHANCEMENT

CONCLUSION

The impetus behind our proposed model for detecting and classifying affected and unaffected potato leaves stems from the urgent need to embrace digitalization in agriculture. As digitalization pervades every sector, it becomes increasingly imperative to integrate it into agriculture for enhanced protection and yield optimization. By leveraging concepts such as activation functions, batch normalizations, convolutional layers, and fully connected layers within CNN-VGG16 architectures, we aim to achieve superior accuracy in disease detection.

The significance of this project transcends mere technological advancement; it holds the potential to revolutionize the agricultural landscape, particularly for the majority of farmers in India who may lack literacy and awareness about disease detection methods. The inability to recognize and address diseases in a timely manner leaves potato crops vulnerable to destruction by pests and pathogens, causing significant hardship for farmers.

We believe that the implementation of our model has the power to transform the plight of potato growers in India. By providing an accessible and efficient tool for disease detection, we empower farmers to safeguard their crops effectively, mitigating losses and ensuring sustainable agricultural practices. In doing so, we not only bolster food security but also contribute to the socioeconomic well-being of farming communities across the nation.

Intelligent Storage Sorting System represents a ground breaking solution for optimizing potato storage conditions. By employing advanced technologies to control temperature, humidity, ventilation, and gas composition within storage facilities, the system ensures that potatoes remain fresh, healthy, and market-ready for an extended period. Through meticulous monitoring and adjustment, it minimizes spoilage, reduces waste, and maximizes profitability for farmers and suppliers. This innovative approach not only improves the quality of stored potatoes but also enhances efficiency and sustainability within the agricultural industry. With its multifaceted capabilities, the intelligent storage system sets a new standard for preserving perishable produce, ultimately benefiting both producers and consumers alike.

FUTURE ENHANCEMENT

The focus will be on optimizing disease detection at the early stages of plant growth to elevate productivity and yield quality. Given the expertise required for disease detection, a smartphone application could prove immensely beneficial. Through this application, farmers could simply capture images of plant leaves and transmit them to a server for automatic identification and classification of diseases. The server would then provide results and recommend appropriate medications directly to the smartphone. To realize this vision, the development of an Android application is planned, ensuring accessibility and ease of use for farmers across India.

Moreover, future end eavors will entail expanding the scope of research to encompass the detection of multiple diseases on a single leaf, as well as localizing diseases and estimating disease severity. Additionally, efforts will be made to enrich the dataset, paving the way for more accurate and comprehensive disease identification. The integration of IoT-based real-time monitoring systems will enable continuous surveillance of plant health, allowing for timely intervention and management.

Furthermore, the development of a dedicated website and mobile application will facilitate seamless access to disease detection services and expert advice for farmers. By leveraging digital platforms, we aim to democratize access to agricultural expertise, empowering farmers with instant solutions to their problems.

In summary, future enhancements will encompass a holistic approach towards disease detection and management, leveraging advancements in technology to provide farmers with timely and effective solutions. Through on going research and development efforts, we seek to enhance agricultural productivity, promote sustainable farming practices, and foster economic prosperity in farming communities.

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