DETECTION OF TOMATO DISEASES LEAF SYMPTOMS USING IMAGE PROCESSING DEEP LEARNING BASED APPROACH

BY

Md. Arifin Islam

ID: 213-25-074

This report is presented in partial fulfillment of the requirements for the Master of Science in Computer Science and Engineering

Supervised By

Dr. Md Zahid Hasan
Associate Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2023

APPROVAL

This Thesis titled "Detection of tomato diseases leaf symptoms using image processing deep learning based approach", submitted by Md. Arifin Islam, ID No: 213-25-074 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 17-01-2023.

BOARD OF EXAMINERS

Dr. S M Aminul Haque, PhD — **Chairman**
Associate Professor & Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Ms. Naznin Sultana — **Internal Examiner**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Mr. Md. Sadekur Rahman — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Mohammad Shorif Uddin, PhD — **External Examiner**
Professor
Department of Computer Science and Engineering
Jahangirnagar University

DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Md Zahid Hasan, Associate Professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Md Zahid Hasan
Associate Professor
Department of CSE
Daffodil International University

Submitted by:

Md. Arifin Islam
ID: 213-25-074
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First I express my heartiest thanks and gratefulness to Almighty Allah for His divine blessing which makes me possible to complete the final year thesis successfully.

I really grateful and wish my profound indebtedness to **Md Zahid Hasan**, **Associate professor**, Department of CSE, Daffodil International University, Dhaka, deep knowledge & keen interest of my supervisor in the field of Machine Learning to carry out this project. His endless patience, scholarly guidance ,continual encouragement , constant and energetic supervision, constructive criticism , valuable advice ,reading many inferior draft and correcting them at all stage have made it possible to complete this project.

I would like to express my heartiest gratitude to **Dr. Touhid Bhuiyan**, Head**,** Department of CSE, for his kind help to finish our project and also to other faculty members and the staffs of CSE department of Daffodil International University.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

Tomato is most popular vegetable all over the world. It's cultivated of high nutritive value. During cultivation tomato leaves expose too many problems and diseases like blight, bacterial spot, early blight, healthy, late blight, leaf mold, sectorial leaf spot ,spider mites two spotted spider mite, target spot, tomato mosaic virus, tomato yellow leaf curl virus etc. So it is necessary to detect these disease so to check their spread and to prevent any undesirable condition. Detection and Identification of these disease on manual level is a very tedious and time consuming process. In this thesis help to understand Detection of tomato diseases leaf symptoms using image processing deep learning-based Approach. I have used tomato leaf as an input value and using artificial intelligence for checking accuracy. My Accuracy rate is 98.1 % on the research of 10490 tomato leaf dataset.

TABLE OF CONTENTS

CONTENTS **PAGE**

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

1.1 Introduction

As Bangladesh mostly depend on Agriculture. Post - independent, the agriculture sector was Bangladesh's big financial driving force. It contributes almost 60% of GDP. Agriculture is critical in Bangladesh for people's livelihood, employment, and GDP contribution; we all know that. Its share has fallen during the previous decade, from 17 percent in 2010 to 12.6 percent in 2020. The industry is essential to our economy, helping to alleviate poverty and provide food security. Tomatoes are one of the most popular crops on the earth. ***Solanum lycopersicum*** is its scientific name, and it grows well in well-drained soil. If we want to detect the disease it so lengthy, time consuming and costly process. Now a days all are want to get fast result. So it is very difficult to identify the disease manually. So if we depend on this methodologies then it might cause for loss of yields and quantity of products. So this thesis helps in detecting dieses in plant which save the time and it does not need any expert for detect the disease manually. In this thesis using some image of various leaf of a tomato plant dataset and different types of symptoms. Train a machine by using some data set. If we input some data detected image as a input value machine can analysis and will get us result using ANN and by analyzing previous train data knowledge easily can classify the accuracy and give us a better result. When a farmer can identify the result and this can prevent the loses and take action against the disease and we can produce the more and more yields. However, the farmers of our country do not understand properly if the tomato plant is growing properly or if it is affected by any disease.

1.2 RESEARCH MOTIVATION

To propose a hybrid model that uses the Gabor wavelet transform approach to extract significant characteristics from images of tomato leaves, as well as support vector machines (SVMs) with Alternate kernel function, to identify real disease kinds which affect tomato plants.

1.3 Research Objective

a) Identify the research lacking's depend on machine learning technique and a great accuracy to identify diseases.

b) To identify and analyses deficiencies in existing machine vision-based methods for correctly detecting various types of tomato leaf diseases using a leaf symptom's.

1.4 Research question

1. Which way do you have detect or identify the real disease using machine learning technique?
2. How can you identify or which method are you uses for develop for detect tomato disease using tomato leaf image?

1.5 Report Layout

Chapter -1: Here in this chapter discussing topics are introduction, research motivation, research objective and question. This chapter represent my thesis paper reflection.

Chapter -2: literature review of different type of related work and scope to solve that problem and challenges which difficulty faced to detect this disease in primary stage are the discussing topics here.

Chapter-3: Highlight about working process, Dataset preparation and different type of data processing layer, Image enhancement technique and histogram.

Chapter-4: In this chapter represent different types of result discussion and lacking's.

Chapter 5: Conclusion and future work.

Chapter 2

Literature Review

2.1 Tomato disease identify previous related works

Several researchers have tried using various techniques in the past to detect illness in tomato leaves, but they have not been successful. This thesis are in India. India ranked second in the production of tomato. Their country tomato production get down because of different types of tomato disease. They used a Convolution Neural Network technique for disease detection and characterization, with 3 max-pooling layers followed by two fully connected layers. The experiment results show that the proposed most pre-trained architectures are VGG16, InceptionV3, and Mobile Net. The classification accuracy is 76% to 100% based on the given class, and the proposed model's overall result is 91.2% for the 9 diseases and 1 normal case. And testing accuracy is 92.2%. They could improve their accuracy to 96-98% [1].

Their research was made on tomato disease detection techniques using a deep learning-based approach. This work represented the CVGAN sample reconstruction model. And plausible synthetic sample generation and an AAR network for tomato disease detection. They used the CVGAN sample reconstruction network and augmentation technique to minimize training sample scarcity and class imbalance. Their accuracy rate is 87.52%. But they didn’t have the better result and they also tries to CNN Algorithm [2].

Their research proposed tomato disease detection using image processing technique, pattern recognition, computer vision and other technologies. Agriculture computer based disease detection they used using different types of CNN algorithm. They used a genetic algorithm for recognition parameters and angles of spectral reflection and shape characteristics to detect disease.AI also used for future learning. Their using Algorithm is K means algorithm to cluster the bounding boxes of tomato disease. Their used filter are ResNet101 to replace VGG16 for extraction. This research can identify single disease only not possible to identify multiple disease at a time. Their accuracy was 98.01% [3].

They proposed a system which used multiple deep CNN techniques used for identify tomato leaf disease. CNN models, ResNet50, InceptionV3, AlexNet and the three versions of MobileNet used for train dataset. The got the highest accuracy by MobileNetV3 by using Adagrad optimizer was 97.81% with a loss value of 0.0088. Raspberry Pi 4. MobileNetV3 used for work station and get better result. MobileNetV3 help to detect the disease. Deploying MobileNetV3 Small on a Raspberry Pi 4 is the first step of research in order to build a handheld device based on IoT and Artificial Intelligence capable of automatic tomato leaf disease detection. Their material and method was confusion metrics, transfer learning and some train dataset [4].

They proposed a system deep learning based approach tomato disease detection using The CNN method with an architecture based on the modified AlexNet may be used to determine the validity of object picture categorization. Their average accuracy value of 96%, precision value of 98%, recall value of 95%, and F-Measure value of 97% confirm this. This algorithm performed a mobile-based Android platform. For this process farmers need to use android phone and input image of affected leaf then the apps use CCN algorithm and Artificial intelligence for give a output and I think this is not so easy to use android phone as a farmer [5].

This thesis proposed SVM model in MATLAB 15a is used. 80 images is used for detect disease one type of disease and totally 320 trained image has used for this detection. 15% images used for sample. With different parameters, the Multi-class SVM was trained. Accuracy rate is 93.78% [6].

Convolutional neural network (CNN) is a significant approach for object recognition in deep learning. They analyze the influence of different depths of CNN architectures on the detection accuracies of plant diseases in this research. Various CNN architectures with varying depths are examined. They are basic CNN baseline (two convolutional layers), Alex Net (five convolutional layers), and VGGNet (with 13 convolutional layers) [7].

This thesis proposed drones based precision farming system effectively identify high disease area in farm using CNN algorithm. Research on 2100 datasets from online, as well as 500 images from a nearby farm has found 99% accuracy when training percentage 85% percent execution speed [8].

This thesis proposed of detect tomato disease using leaf. They used CNN model and their using layer for processing image are max pooling, Netres50, VGG16, InceptionV3 etc. Their classification Depending on the class, the accuracy ranges from 76% to 100%, and the proposed model's average accuracy is 91.2% for the nine disease and one healthy classes [9].

2.2 Scope of the Problem

Detection of tomato disease is difficult process because different types of tomato disease are available.

2.3 Challenges

I have faced several difficulty with this study found, which is following:

a) **Similar symptoms:** A variety of diseases can produce similar leaf symptoms, making it challenging to identify the precise condition at hand.

b) **Variable symptoms:** Depending on the disease's stage, the tomato variety, and the environment, a disease's symptoms may change.

c) **False positives:** Due to errors in the data gathering and classification, there may also be false positive results.

d) **Damage from a variety of sources:** The signs and symptoms of a disease may resemble those brought on by other conditions, like insect stings, vitamin deficits, or environmental stress.

e) **Environmental variables:** Because diseases are affected by environmental elements like temperature, humidity, and light, it can be challenging to diagnose an illness solely only on symptoms.

f) Infection level or disease of life cycle determination.

g) **Data collection:** There are no reference data sets for categorization accessible online. As a result, creating a photographic record in the field of tomato leaf disease has become extremely challenging.

h) **Raw image processing:** The complete picture of the particular reagent is often exaggerated, making it extremely clean. So it's your job to collect the most complete photographs and enhance your categories through scoring and noise.

i) **Select machine learning approach:** Some researchers employ novel systems to learn techniques for quickly completing assignments. As a result, by selecting the most promising approach to the method's knowledge, one may efficiently identify and detect tomato leaf syndrome.

j) **Accuracy Improvement:** Another tough challenge was improving the system's accuracy through version knowledge and the use of Gaussian noise because 98% accuracy had already available.

In order to overcome these difficulties, it is crucial to use a variety of illness detection techniques, such as visual inspections, laboratory testing, and the application of computer vision-based technologies like deep learning. Furthermore, combining symptom-based and pathogen-based diagnostics can improve disease detection precision.

CHAPTER 3

Materials and Methodology

3.1 Working Process

There are five working process in my thesis these are:

1. Input image or collect prepared image or dataset
2. Image pre processing
3. CNN architecture (Apply machine learning algorithm)
4. Training and testing data processing
5. Accuracy checking.

The entire workflow, from image acquisition to image analysis, is shown in Figure 1 and detailed in the next section.

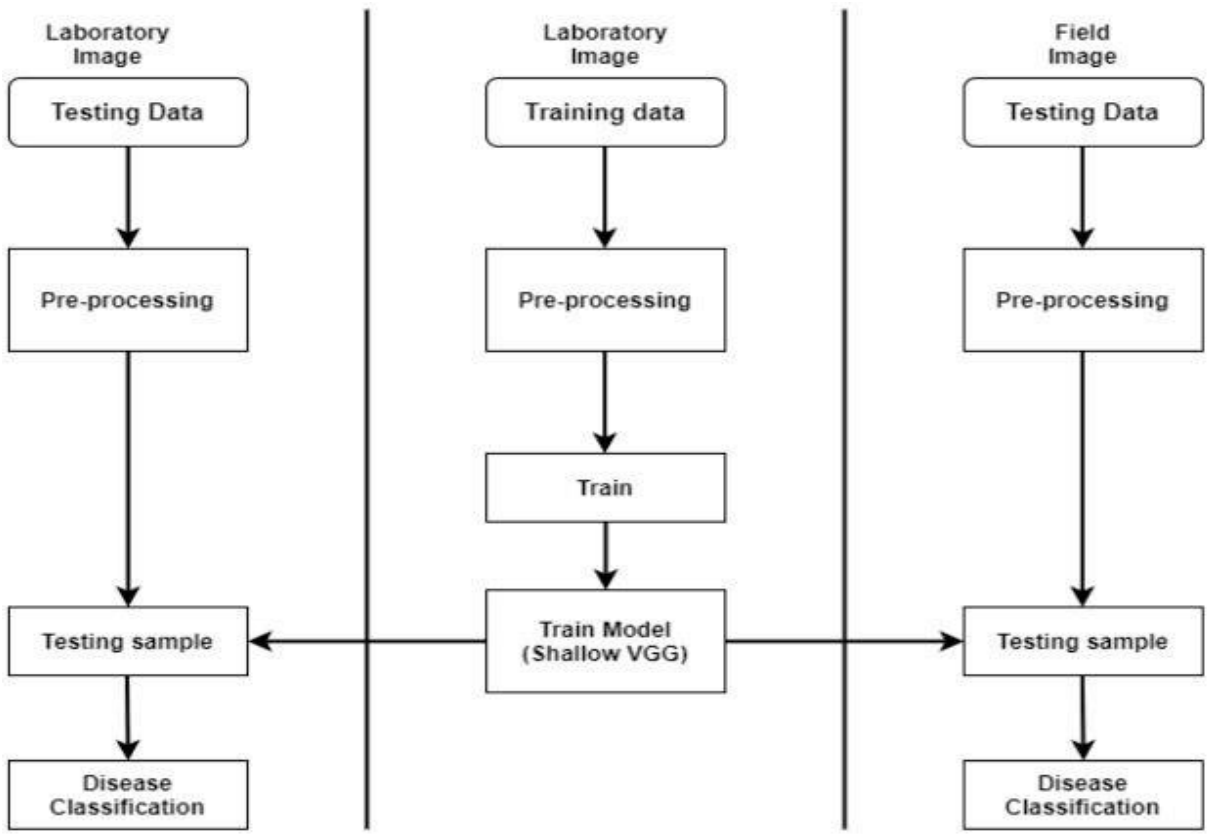


Figure 3.1: Working process model

The following steps are routinely used in order to diagnose tomato leaf diseases using leaf symptoms:

Sample collection: For analysis, tomato plant leaves exhibiting disease symptoms are gathered. To take a representative sample from the field or greenhouse, it is crucial to gather samples from various points around the space.

Observation of symptoms: Leaf discoloration, spotting, withering, and curling are among the symptoms that are looked for in the gathered leaves. The location of the symptoms on the leaf should be noted because it may reveal information about their origin.

Pathogen identification: If a pathogen is thought to be the source of the symptoms, laboratory tests like PCR or ELISA may be employed to pinpoint the precise pathogen in question.

Confirmation: Following pathogen identification, additional tests, such as pathogen-inoculation studies or host range analyses, can be carried out to ensure that the pathogen is indeed the source of the symptoms.

Management: After the existence of the illness is established, a plan for containing its spread can be designed. Possible strategies include the use of resistant plant cultivars, cultural precautions, or chemical control.

Monitoring: It's critical to regularly check the crop for new infections and to gauge how well the management plan is working.

3.2 Dataset Preparation

After collected the data set I have prepared dataset for training and this is very important part of my thesis .Firstly I have prepared some data set using known infection of tomato leaf disease and a healthy image data set. So that when I check the preprocessing image then machine can compare the train image. I worked on a dataset which collected from kaggle on various tomato leaf symptoms and a healthy leaf.

I have used 10490 train dataset from kaggle and 500 image segmentation (divided into some different pixel image) data.

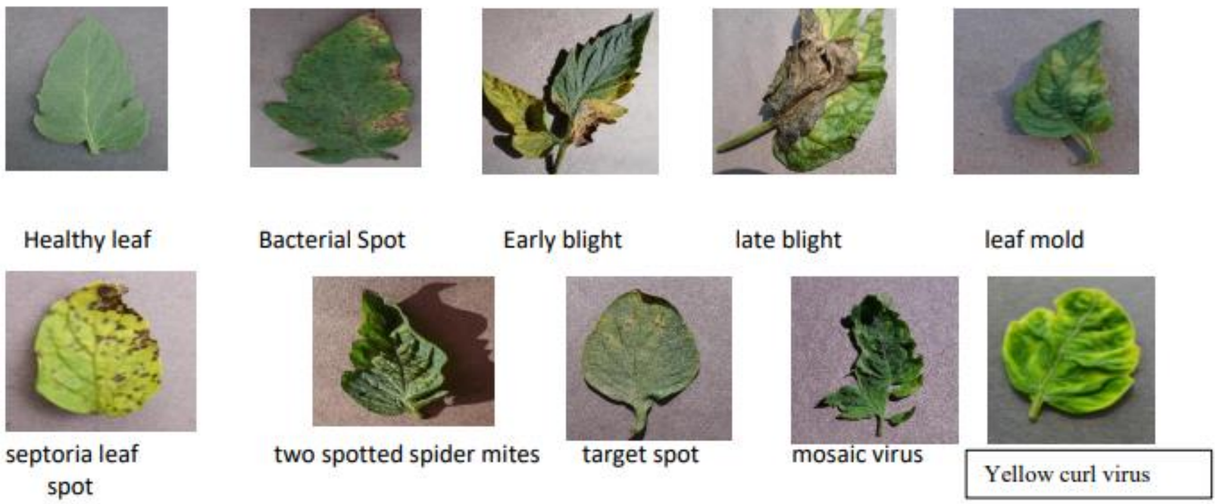


figure 3.2. Class wise sample image of the dataset

3.3 Image Pre-processing

Image preprocessing is used for the detection of tomato plant disease. In minimally reflective imaging, where the input and output are equivalent penetration images, preprocessing is a phenomenon that is taken into consideration.

One of the least researched topics in the data science world is image data processing. Every developer has a unique method for carrying out tasks. For image pre-processing, some of the tools and frameworks utilized include Python, Pytorch, OpenCV, Keras, Tensorflow, and Pillow etc. Always require data while developing a machine learning. Picture information in this scenario. Unfortunately, complexity, accuracy, and mismatches are some issues occurs with image data. That’s why we need to preprocessing for clean image for get a better result.

3.3.1 Picture or Image Enhancement Method

Contrast is enhanced via histogram equalization, often called grayscale conversion. With the help of this technique, the penetration stages may be distributed uniformly throughout the penetration measurement. Because the histograms in the next frame are so similar, adjusting it may provide poorer results than the first. Faint regions might lead to large peaks in the histogram. As a result, histogram balancing may add extra picture noise. This indicates that, in contrast to its neighbors, it does not adapt to the building. If there are usually limited decreased pixels in a particular dark area, minor differential contrast can be totally lost.

In this approach, the picture is divided into rectangles or image parts, and histogram equalization is applied to each of the individual image parts or image parts. In this instance, bilinear separations or discontinuities are the only sources of artifact interference between consecutive blocks.

3.3.2 Contrast Limitation and Adaptive Histogram Equalization

In order to address the issue of noise across clip boundaries, the CLAHE approach was employed. To improve the histogram to preset levels, it is trimmed as much as possible before computing the cumulative distribution function. CLAHE precomputes the CDF and extracts the histogram with defined values to limit the gain. This restricts the CDF's slope, which transforms the function. By normalizing the histogram and thereby the size of the neighborhoods, the clipping limit, or value at which the histogram is clipped, is established. CLAHE makes use of two important factors: block size and clip limits. These two factors determine the image's quality.

3.4 Artificial Neural Network

Artificial neural networks, often known as neural networks or neural nets, are computing systems inspired by the organic neural networks seen in animal brains.

ANNs are formed of artificial neurons which are basically constructed from biological neurons. Each artificial neuron receives and sends a single signal, which may be shared by several neurons. The input might be feature values from an external data sample, such as images or documents, or they could be neuron outputs. The last output neurons of the neural net finish the task, such as recognizing an object in a photograph.

To compute the neuron's output, multiply the weighted sum of all inputs by the weights of the connections from the inputs to the neuron. We then add a bias term to this sum. This weighted sum is often referred to as the activation. The weighted total is then passed through an activation function to produce the output. Photographs and papers are utilized as first inputs. The task is completed by the final outputs, such as recognizing an object in a photograph.

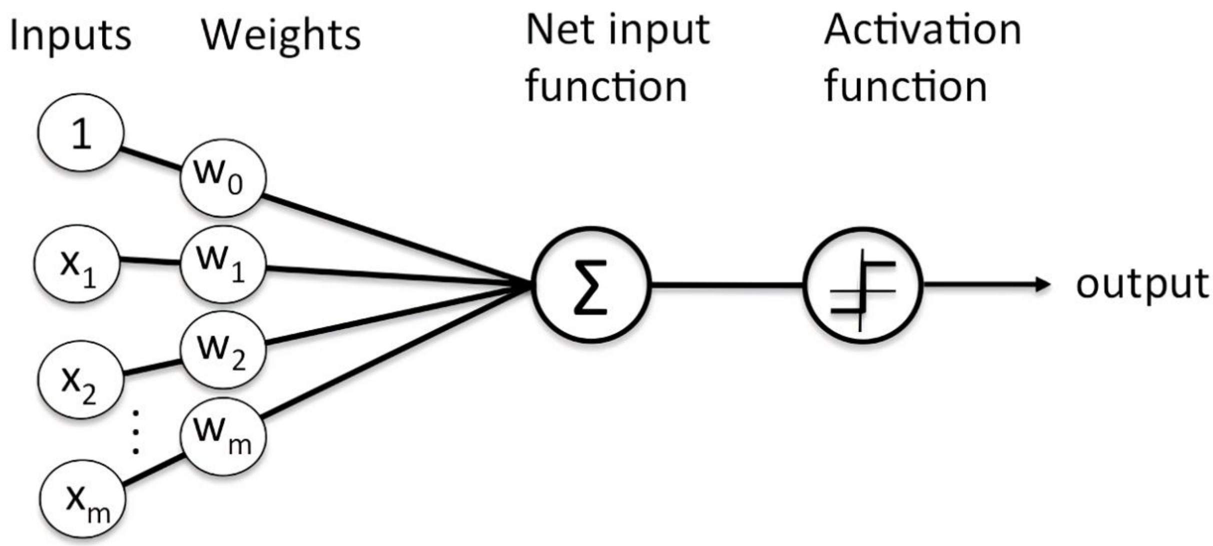


Figure 3.4. Artificial Neural Network

3.5 Convolutional Neural Network

A unique variety of artificial neural network known as a convolutional neural network mixes the standard matrix multiplication in one or more layers with the convolution math operation. It is used for picture recognition and processing and is specifically intended to process pixel data. Multilayer perceptron's normalized version, CNN.

A completely linked network is typically referred to as a multilayer perceptron. In other words, every neuron in one layer is linked to every neuron in the layer above it. These networks are susceptible to data overfitting due to the fact that "everything connects" inside them.

Common techniques for preventing or controlling overeating include disabling or penalizing training metrics (such as weight reduction) .CNN approaches regularization differently. Structured data models and compressing smaller, simpler samples allow CNNs to gain from increasingly complex model sets. It filter CNN connections are therefore the least difficult and largest connections.

3.5.1 Convolutional Layer

As illustrated in Figure 4, Updated Convolutional Neural Network process applied in my thesis. This process have two max pooling layers, one input layer, two convolution layers, one hidden layer, one flattening layer, and an output layer.

Different sorts of tomato leaves were entered into the input layer. To extract picture information without loss, the image collection was subjected to a padding procedure. It expanded the picture by one pixel around the supplied image. Padding is frequently applied in two ways: zero padding and surrounding pixel values. The tomato leaf graphics were surrounded by zero padding in this case. This aided us in obtaining same size input continuously. As a result, elements of whole input photos handled without serious loss of feature to finish the convolution process, convolutional filter, often known as kernels, are used to the padded input data. The size of convolutional filter was 3×3 in size, strides of the one and there are 32 unique convolutions. Both Convolutional layers used convolution filters.

The output was convolutional before being delivered to the activation. Because it can detect highly complicated patterns, an activation function was created. Utilized to induce nonlinearity within the network. In a CNN, it modifies the feature map values. There are several types of activation functions. The activation function wastrel was used in the two-layer curve technique. The feature maps were subjected to a maximum pooling filter. Table 1 depicts the architecture of Convolutional Neural Networks. The number of recovered features in the first and second convolution layers was 896 and 9248, respectively. The flattening layer flattened the obtained tomato leaf picture features. The dense layer, also known as the completely connected layer, was applied.

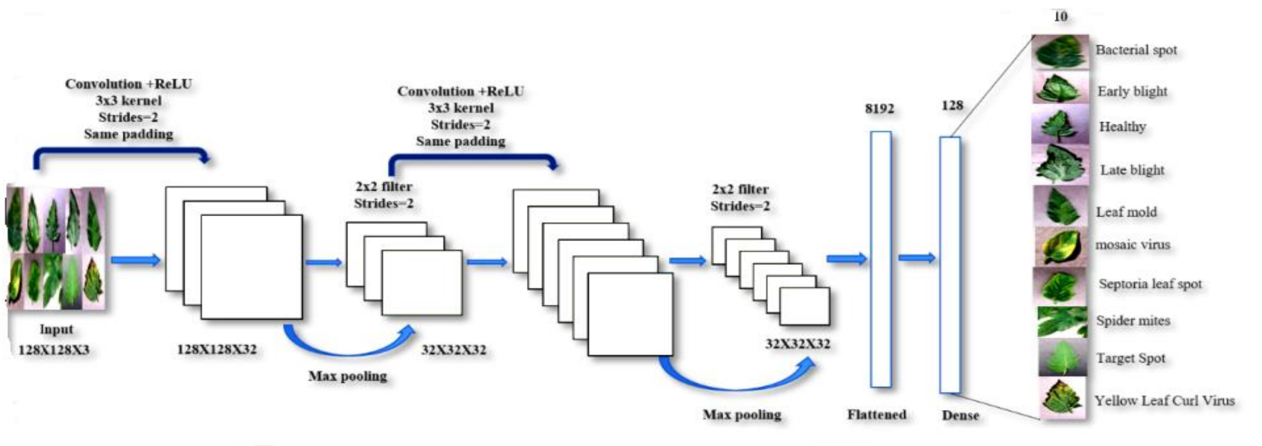


Figure 3.5.1: Convolutional Neural Network Process.

3.5.2 Maxpool Layer

A 2-D max pooling layer down samples the input by splitting it into rectangular pooling areas and determining the maximum of each zone.

a) The layer pools use for Second Dimensional picture input (4 dimensional data split into 2 dimensional).

b) For sequence input the Pools layer for 2-D picture. (Data with five dimension split with 2 dimension).

c) For 1 dimension sequence input (4 dimension corresponding to 1 dimension with pixel, spatial dimension, channels, observation and time steps).

3.5.3 Completely Connected Layer

A completely connected layer in a neural network is a form of layer where every neuron in the layer is connected to every neuron in the layer below it. This type of layer is also referred to as a dense layer or a fully connected layer (fc layer). All of the neurons in a layer that is fully linked receive input from the neurons in the layer below them, and the output of each neuron in that layer is supplied as input to all of the neurons in the layer above.

Each neuron in fully connected layers has a set of weights that are used to calculate the output, which is then processed by an activation function. In order to reduce the error between the projected output and the actual output, these weights are learned throughout the training phase. The amount of output values generated by the fully linked layer, which can serve as an input for the following layer, is determined by the number of neurons in that layer.

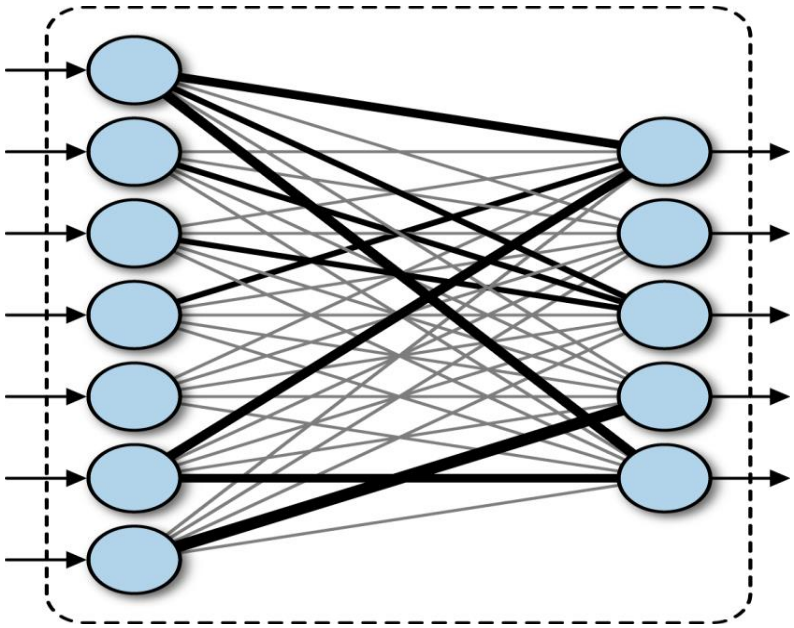


Figure 3.5.3 Fully Connected Layer image.

3.6 Transfer Learning

Communication is frequently used to obtain information about a technique that leverages established, ancient, and continuing know-how to solve an issue and is repeated as the first way to solve a problem on another topic. Deeply integrated neural community mode might take days or weeks to train on very large disk sets. One technique to decrease this system is to reuse version weights in pre-trained modifications that have been improved on popular and imaginative test cases that are loved on laptops like ordinary chores. Image a clear image. You may utilize the top-notch actor mod right now, or switch to the new version on computers with imagination and projection issues.

3.6.1 VGG16

There are two VGG modes: VGG-16 and VGG-19. VGG-16 was utilized to categorize the dataset in this study. VGG-sixteen is structured of three layers: a convolutional layer, a merged layer, and a completely associative layer. Convolution Layer: This layer uses filters to extract features from a picture. The most significant factors are scale and kernel peak. Full Layer: Its function is to shorten the distance between nodes in order to lower the parameters and computational scope inside the network. Fully Connected: A fully connected link is completely connected to the preceding layer, as in a basic neural network. The construction of the model is depicted in this picture.

3.6.2 Resnet50

ResNet50 is continuous Neural Network with 50 layers (48 convolutional layers and 1 MaxPool layer and 1 intermediate group). Residual Neural Network (ResNet) is an ANN that bureaucratizes communities by superimposing redundant blocks on top of one other. The ImageNet database contains over one million pre-selected photographs that may be downloaded. Pre-qualified communities may sort photographs into thousands of categories, such as keyboards, mouse, pencils, and diverse animals. Images produced by the community are 224 x 224 in size.

3.6.3 InceptionV3

Inception v3 is a strong and deep neural network that can categorize irrelevant label photos from the Image Net dataset. Only one v3 model was published in 2015, and it includes 42 instructions and a reduced mistake rate than its predecessor. Let's see whether the different optimizations help the V3 model. Fixes for the Inception V3 style:

a) Split it into numerous little loops.
b) Spatial multiplication in odd convolutions
d) The efficiency of auxiliary classifiers
d) Decreasing effective communities

3.7 Training and Testing

The training and testing layers of a neural network refer to the procedures used to train and assess the model's performance.

Firstly, I have divided my data set into two parts and these are training and testing datasets. This data set partitioning strategy is utilized at random when the training set consists of around 100 tomato leaf image pictures, 80% is used to train the model and 20% is used for training.

Model education Formalized paraphrase the test was two times. Raw image used for contrast enhanced as much as possible.

Transfer learning is used to train all models.

As indicated in the equation, all approcech are trained for transfer learning by categorical cross-entropy as the loss function (1). The learning rate is set to 0.001, and the loss function is categorical cross-entropy, as given equation (1).

The rate of learning is set at 0.001.

$$L_{CE} = -\sum_{i=1}^{n} ti \log (Pi) \quad (2)$$

SoftMax is utilized as the activation function in the Adam optimizer for all of the designs presented in equation (2)

$$f_i(\overrightarrow{a}) = \frac{e^{a_i}}{\sum_k e^{a_k}} \quad .(3)$$

Figure 1 depicts the full test method. The entire test is run using a 64-bit Windows operating system, an Intel Core i7-1065G7 CPU, 16GB of RAM, and a 512GB SSD hard disk with Python programming. The Google Colab environment's language.

CHAPTER 4

Experiments Result and Discussion

4.1 Results and Discussion

Primarily, the architecture, method and algorithm was trained using various scaled input image size. Input image or picture size was 256×256. Finally, input picture real measurement was fixed to 128×128 cause CNN model Picture input size was that scale. On the other hand others member model was made during back propagation it was without weight optimization.

Tomato crop Plant Village dataset had a variety of picture ratios. All of the photos were obtained for training and validation purposes. The model's performance was hampered .The total number of images captured every single class was 300 dpi in order to provide a proper dataset. The data split ratio for testing and training was 70:30.

The Convolutional Neural Network model was applied with varied century of 100, 200, and 300, as shown in Table 2. This model's test accuracy loss in 100 century are 0.944 and 1.0017. The sample testing accuracy and loss in 200 century was 0.62112 and 0.97581. In the time of trained dataset with 300 century this method accuracy and loss are 0.93011 and 0.84782.

Based on the variables listed above, the model achieved excellent accuracy and low loss in 300 epochs of training and validation.

Follow the figure 3 the same result respectively.

Table 4.1.1 Training and validation accuracy and training and validation loss in CNN model.

Century	Training		Validation		Time per ms
	Loss	Accuracy	Loss	Accuracy	
100	0.9861	0.5671	1.00171	0.49441	19,2891ms
200	0.9612	0.6942	0.98582	0.62112	19,2871ms
300	0.9031	0.9861	0.93011	0.84781	28,4291ms

The confusion matrix was then produced to visualize the classification performance of the tomato leaf dataset using CNN, as shown in Figure 3. The number of correctly categorized photos in 100 epochs during validation and training was 568 and 1636, respectively. The number of correctly categorized photos in 200 epochs during validation and training was 665 and 1855, respectively. During validation and training, there were 723 and 2083 properly classified pictures in 300 iterations, respectively.

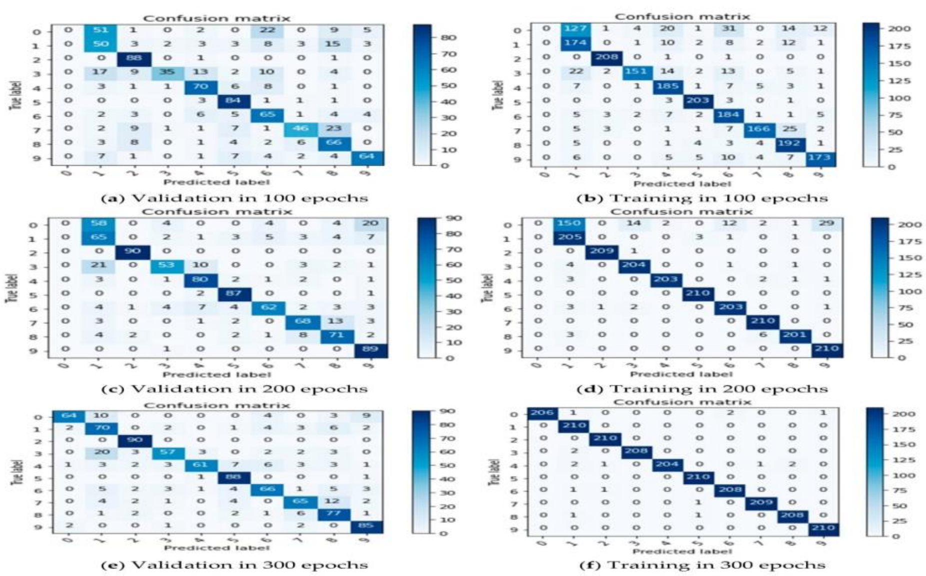


Figure 4.1.1 shows a graphical depiction of the CNN model's performance.

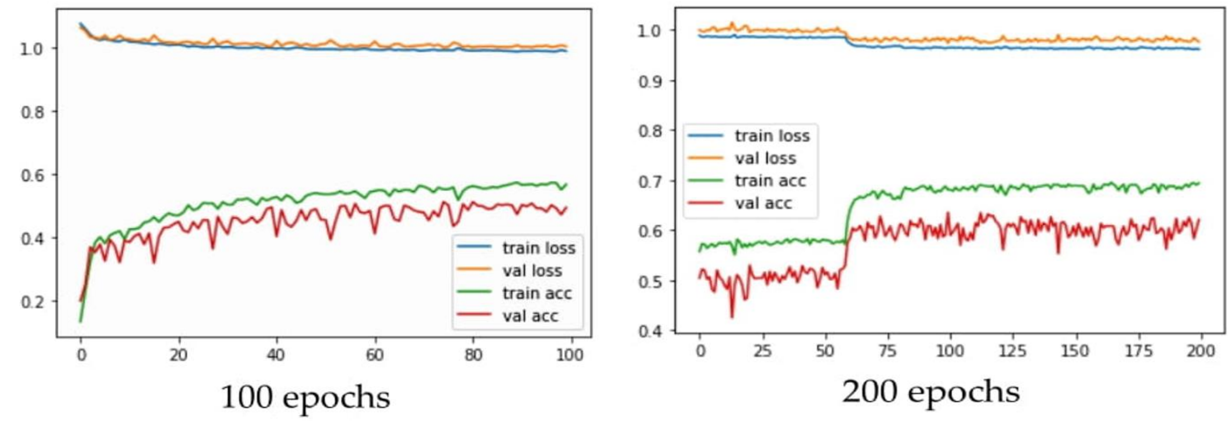


Figure 4.1.2 Confusion matrix of validation and training in different epochs

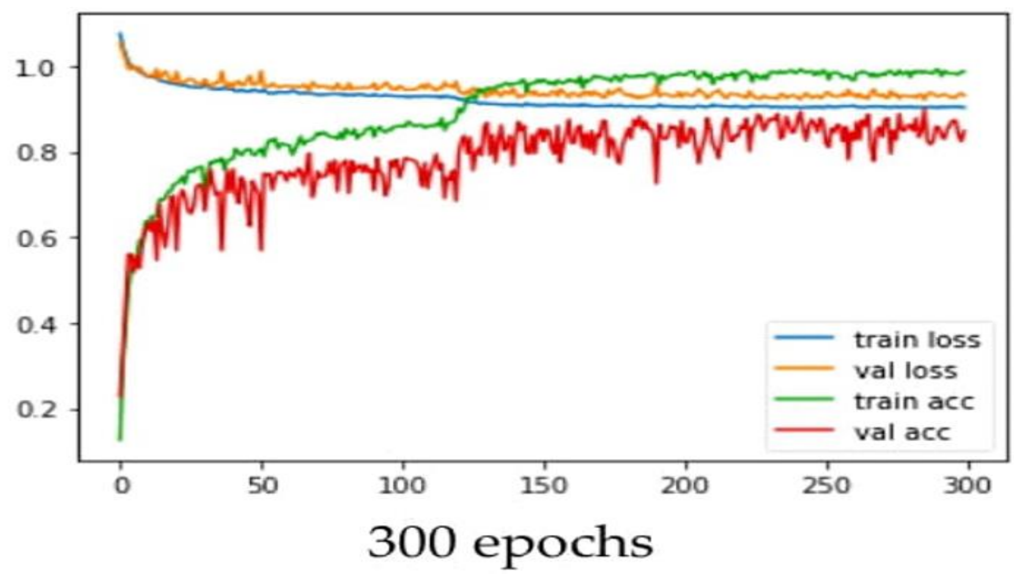
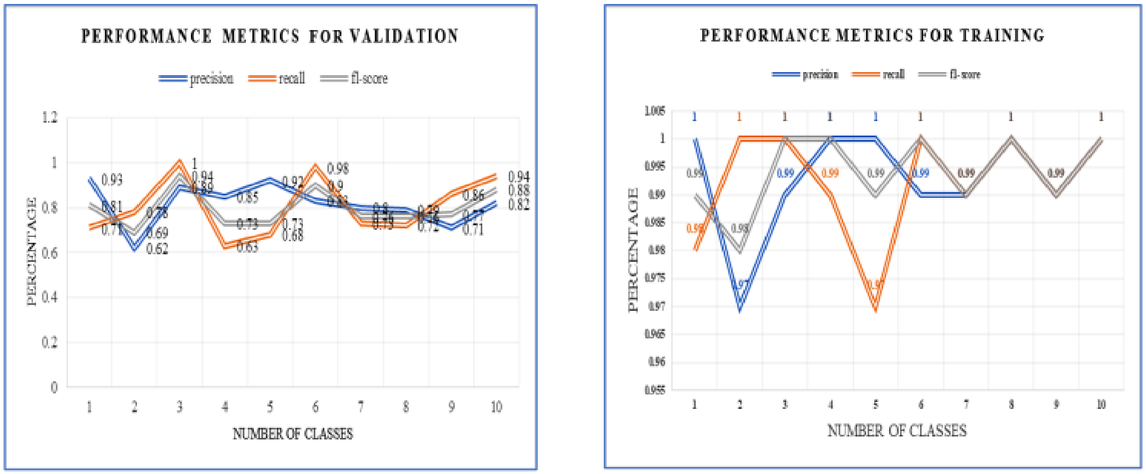


Figure 4.1.3 CNN Model Graphical View.



(a) (b)

Figure 4.1.4 Training Accuracy and Validation Graphical view

Other matrices accuracy are available in f1 score M. Averages and Weighted averages. The performance of a CNN model cannot be determined just by its accuracy. As a consequence, these measures were examined as validation and training outcomes for three hundred century are provided in Tables 3 and 4. To get the best outcome, precision values, recall values, and f1 score measures were examined. A graphical illustration of the comparison is shown in Figures -8 of a and b graphical view part.

Table 4.1.2: Validation of performance matrices

Class No.	Precision Value	Recall Value	F1 Score	Total Support
0	0.930	0.710	0.810	90
1st	0.620	0.780	0.690	90
2nd	0.881	1.0	0.940	90
3rd	0.850	0.630	0.730	90
4th	0.921	0.680	0.730	90
5th	0.830	0.980	0.90	90
6th	0.810	0.731	0.760	90
7th	0.790	0.722	0.760	90
8th	0.711	0.861	0.770	90
9th	0.821	0.941	0.880	90
Accuracy			0.821	900
M. Average	0.821	0.821	0.821	900
Weighted Average	0.821	0.821	0.821	900

Table 4.1.3: Training of performance matrices and result

Class No.	**Precision value**	**Recall value**	**Fl Score**	**Support**
00	1.0	0.910	0.991	1000
1^{st}	0.970	1.0	0.980	1000
2^{nd}	0.991	1.0	1.0	1000
3^{rd}	1.0	0.990	1.0	1000
4^{th}	1.0	0.970	0.991	1000
5^{th}	0.990	1.0	1.0	1000
6^{th}	0.990	0.990	0.991	1000
7^{th}	1.0	1.0	1.0	1000
8^{th}	0.990	0.990	0.991	1000
9^{th}	1.0	1.0	1.0	1000
Accuracy Value			0.991	10000
M. Average	0.991	0.991	0.991	10000
Weighted Average	0.991	0.991	0.991	10000

CHAPTER – 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINBILITY

5.1 Impact on Society

The use of image processing and deep learning-based techniques to identify tomato leaf diseases has the potential to have a huge influence on society by allowing farmers to diagnose plant diseases more rapidly and correctly. This can lead to more effective use of resources like water and pesticides, resulting in increased agricultural yields and greater food security in the long run. Furthermore, these technologies can aid in the reduction of plant disease transmission, which can have a severe influence on agricultural productivity as well as the environment.

5.2 Impact on Environment

Using image processing and deep learning-based techniques to identify tomato leaf illnesses can benefit the environment by allowing farmers to more precisely diagnose plant diseases and take necessary action to prevent them from spreading. This can result in the usage of less pesticides, which can be damaging to the environment, and can assist to conserve biodiversity and ecosystem health. Furthermore, these technologies can assist to reduce water use and boost crop yields, both of which can help to lessen agriculture's environmental effect.

5.3 Sustainability

Tomato infections may be discovered using image processing and deep learning approaches. Image processing techniques may be used to extract characteristics from photos of tomato plants, while deep learning algorithms can be used to categorize the images depending on the presence or absence of illness. This strategy is sustainable since it can be automated, eliminating the need for manual inspection, and it can also be used to swiftly identify disease outbreaks, helping to prevent them from spreading. Furthermore, by employing deep learning algorithms that are trained on massive volumes of data, the system may improve over time, making it more accurate and efficient.

CHAPTER-6

Conclusion and Future Work

6.1 Conclusion

Deep-learning methods are used to identify and diagnose tomato leaf disease. This type of disease identification in the tomato crops CNN model alternative learning approaches such as ResNet152, VGG19, and InceptionV3 etc. This method has a 98% training accuracy and an 88.17% testing accuracy and validation accuracy 98.12%. Farmers may really solve plant identification challenges without the assistance of plant experts. This will assist them in curing tomato plant infections in a timely manner, allowing them to enhance the product quality enhance the quantity of the profit. We enhance the model in the future by using a different crop. In addition, we will attempt to enhance the test by optimizing the same model on the same dataset.

6.2 Future Work

If the illness can be detected using tomato leaves, crop productivity can be greatly boosted. It will make a significant contribution to the national economy, therefore I will work on how to diagnose this further in the future. Working using mobile phones and computers to allow anybody to identify illnesses using the leaves of various crops.

REFERENCES

[1]. M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "TOLED: Tomato Leaf Disease Detection using convolution neural network," *Procedia Computer Science*, vol. 167, pp. 293–301, 2020.

[2]. G. YILMA, S. BELAY, K. U. M. I. E. Gedamu, M. ASSEFA, M. AYALEW, A. OLUWASANMI, and Z. QIN, "Attention augmented residual network for tomato disease detection and classification," *TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES*, vol. 29, no. SI-1, pp. 2869–2885, 2021.

[3]. Y. Zhang, C. Song, and D. Zhang, "Deep learning-based object detection improvement for tomato disease," *IEEE Access*, vol. 8, pp. 56607–56614, 2020.

[4]. H. Tarek, H. Aly, S. Eisa, and M. Abul-Soud, "Optimized deep learning algorithms for tomato leaf disease detection with hardware deployment," *Electronics*, vol. 11, no. 1, p. 140, 2022.

[5]. Chen, H.-C. *et al.* (2022) "Alexnet convolutional neural network for disease detection and classification of Tomato Leaf," *Electronics*, 11(6), p. 951. Available at: https://doi.org/10.3390/electronics11060951.

[6]. Vetal, S. and R.S., K. (2017) "Tomato plant disease detection using image processing," *IJARCCE*, 6(6), pp. 293–297. Available at: https://doi.org/10.17148/ijarcce.2017.6651.

[7]. Suryawati, E. *et al.* (2018) "Deep structured convolutional neural network for Tomato Diseases Detection," *2018 International Conference on Advanced Computer Science and Information Systems (ICACSIS)* [Preprint]. Available at: https://doi.org/10.1109/icacsis.2018.8618169.

[8]. Hasan, M., Tanawala, B. and Patel, K.J. (2019) "Deep learning precision farming: Tomato leaf disease detection by transfer learning," *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.3349597.

[9]. Sakkarvarthi, G. *et al.* (2022) "Detection and classification of tomato crop disease using convolutional neural network," *Electronics*, 11(21), p. 3618. Available at: https://doi.org/10.3390/electronics11213618.

Plagiarism Checked by Md. Zahid Hasan, Associate Professor, Department of CSE Daffodil International University	

DETECTION OF TOMATO DISEASES LEAF SYMPTOMS

ORIGINALITY REPORT

20%	16%	14%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.mdpi.com Internet Source	3%
2	en.wikipedia.org Internet Source	2%
3	mdpi-res.com Internet Source	2%
4	dspace.daffodilvarsity.edu.bd:8080 Internet Source	1%
5	Yang Zhang, Chenglong Song, Dongwen Zhang.. "Deep Learning-based Object Detection Improvement for Tomato Disease", IEEE Access, 2020 Publication	1%
6	digilib.esaunggul.ac.id Internet Source	1%
7	Ravi Kishore Kodali, Princy Gudala. "Tomato Plant Leaf Disease Detection using CNN", 2021 IEEE 9th Region 10 Humanitarian Technology Conference (R10-HTC), 2021 Publication	1%