

LEAF DISEASE DETECTION USING DEEP LEARNING

BY

NIHARANJAN SARKER

ID: 161-15-7654

IMRANA HAQUE

ID: 161-15-7661

AND

NUSHRAT UDDIN

ID: 161-15-7660

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Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Md. Zahid Hasan

Assistant Professor

Department of CSE

Daffodil International University



DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled “**BETEL LEAF DISEASE DETECTION USING DEEP LEARNING,**” submitted by Niharanjan Sarker, ID no: 161-15-7654, Imrana Haque Sayama, ID no: 161-15-7661, Nushrat Uddin, ID no: 161-15-7660 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 Master of Science in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 7th October 2020.

BOARD OF EXAMINERS



Dr. Syed Akhter Hossain

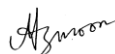
Professor and Head

Department of Computer Science and Engineering

Faculty of Science & Information Technology

Daffodil International University

Chairman



Nazmun Nessa Moon

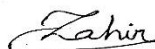
Assistant Professor

Department of Computer Science and Engineering

Faculty of Science & Information Technology

Daffodil International University

Internal Examiner



Gazi Zahirul Islam

Assistant Professor

Department of Computer Science and Engineering

Faculty of Science & Information Technology

Daffodil International University

Internal Examiner



Dr. Md. Saddam Hossain

Assistant Professor

Department of Computer Science and Engineering

United International University

External Examiner

DECLARATION

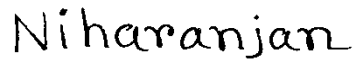
We hereby declare that, this project has been done by us under the supervision of **Md. Zahid Hasan, Assistant Professor, Department of CSE**, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree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

Supervised by:

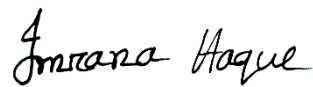


Md. Zahid Hasan
Assistant Professor Department of CSE
Daffodil International University

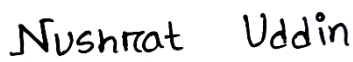
Submitted by:



Nihararjan Sarker
ID: 161-15-7654
Department of CSE
Daffodil International University



Imrana Haque Sayama
ID: 161-15-7661
Department of CSE
Daffodil International University



Nushrat Uddin
ID: 161-15-7660
Department of CSE
Daffodil International University

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ABSTRACT

The main objective of this project is to construct a system to detect the betel leaf diseases which are leaf spot or anthracnose, bacterial leaf spot and leaf stem. This project concentrate on the image processing techniques used to improve the quality of the image and neural network technique to classify the disease. The methodology is based on tensorflow and retraining image classifier using convolutional neural network. The model has been trained on three different disease of betel leaf. When a sample test image will be given it will test the image using the trained convolutional network model. Consequently, by implementing the technique leaf diseases are recognized about 90 percent accuracy rates.

TABLE OF CONTENT

CONTENTS	PAGE
Board of examiners	i
Declaration	ii
Acknowledgements	iii
Abstract	iv
Table of content	v
List of figures	vii
List of tables	viii
 CHAPTER	
CHAPTER 1: INTRODUCTION	01-04
1.1 Introduction	01
1.2 Motivation	02
1.3 Rationale of the Study	02
1.4 Expected Output	03
1.5 Report Layout	04
 CHAPTER 2: BACKGROUND	05-07
2.1 Introduction	05
2.2 Literature Review	05
2.3 Scope of the Problem	07
2.4 Challenges	07
 CHAPTER 3: BETEL LEAF DISEASE AND SYMPTOMS	08-11
3.1 Introduction	08
3.2 Discussion of diseases	08

CHAPTER 4: RESEARCH METHODOLOGY	12-22
4.1 Introduction	12
4.2 Research Subject and Instrumentation	12
4.3 Data Collection Procedure	14
4.4 Implementation Requirements	16
4.5 Inception V3 Model	16
4.6 Data Augmentation	17
4.7.1 Retraining image classifier	17
4.7.2 Activity Diagram	21
4.8 Discussion	22
CHAPTER 5: EXPERIMENTAL RESULTS AND DISCUSSION	23-27
5.1 Introduction	23
5.2 Experimental Results	23
5.3 Confusion Matrix	25
5.4 Descriptive Analysis	26
5.5 Summary	27
CHAPTER 6: LIMITATIONS, CONCLUSION, IMPLICATION FOR FUTURE STUDY	28-29
6.1 Limitations	28
6.2 Conclusions	28
6.3 Implication for Further Study	29
REFERENCES	30

LIST OF FIGURES

FIGURES	PAGE NO
Figure 3.1: Betel Leaf Stem	9
Figure 3.2: Betel leaf Spot or Anthracnose	10
Figure 3.3: Bacterial Leaf Spot	11
Figure 4.1: Convolutional Operation	13
Figure 4.2: Max Pooling	14
Figure 4.3: Raw Betel Leaf images	15
Figures 4.4: Inception V3 Model	17
Figures 4.5: Retraining Image Classifier From Terminal	18
Figure 4.6: Retraining Image Classifier From Terminal	18
Figure 4.7: Image Upload Activity Diagram	21

LIST OF TABLES

TABLE	PAGE NO
Table 4.1: The raw betel leaf dataset	15
Table 5.1: Confusion Matrix	25

CHAPTER 1

INTRODUCTION

1.1 Introduction

Betel vine (*Piper betle*L.), a member of the Piperaceae, is also known as pan. There are approximately 100 types of betel leaf (pan) the world over of which 40 are encountered in India and 30 in west Bengal and Bangladesh [1]. Betel vines are developed all through Southeast Asia in plots whose territory is generally 20 to 2000 square meters (0.005 to 0.5 section of land). The betel leaves resemble gold. Betel leaves are a very important crop in the economy of Bangladesh. The delicious betel leaves of Rajshahi division are always highly valued. In Bangladesh, betel leaf cultivating yields differ by district and vine assortment. In one locale where betel leaf development is the fundamental wellspring of pay for farmers, an aggregate of 2,825 hectares of land is committed to betel vine cultivating. Betel leaf contains vitamin c, thiamine, niacin, riboflavin, and carotene and is a source of calcium also. So it helps in the treatment for various diseases.

During cultivation betel leaves are mainly affected by three diseases such as leaf spot or anthracnose, leaf rot and bacterial leaf spot which cause a great loss for the farmers. However, due to lack of research, many farmers have lost their ability to protect their betel leaves. Therefore, if proper research and initiatives are taken, betel leaves can revolutionize the economy. So the aim of this paper is to study and identify betel leaf diseases using deep convolutional neural network (CNN).

1.2 Motivation

Now is the time of technological revolution. In the present advanced age, it is a lot of significant that the cultivating is blended in with the most elevated level innovation and ranchers get the opportunity to utilize the most recent innovation for productive administration of their yields. The utilization of data access through smart phones among the farmers has expanded as of late, which has had a beneficial outcome on the yield of the creation. In any case, there is as yet a lacking of information sharing between the farmers and the farming specialists while it goes ahead a subject of appropriate yield the board. Because of the difficulties in preparing the ranchers on a mass level on subjects like ailment distinguishing proof and their administration. Again the farmers living in the remote area, they are not interested to connect to agriculture expert or it is impossible for them to connect physically. As a result, in the greater part of the cases the farmers depend on their past experience and instinct for choice on distinguishing crop diseases and their therapies. Our inspiration of this paper is to give the farmers the admittance to a help from anyplace which will identify the sickness promptly for serving their requirements on viable administration of infection. As an initial step, this framework centers on making assistance for the executives of Betel leaf maladies utilizing smart phones.

Image processing techniques have been applied in this system for identification of three Betel leaf ailments named Leaf stem, Leaf Spot or Anthracnose, Bacterial leaf spot. It is conceivable to make this a self-sufficient framework for malady recognizable proof and giving proposals dependent on image processing reports that are why we have taken this step for their problems regarding Betel leaf cultivation.

1.3 Rationale of the Study

As we already know that, Betel leaf is one of the most important crops of many countries, but the production of Betel leaf still too low because of disease. The main reason behind this is farmers still rely on the old process when any leaf is affected and because of proper way to taking care of them without knowing the disease of Betel leaf.

As a result, most of the cases they make the misuse of various medicines to remove the disease. Most of the times farmers don't take the advice of Betel leaf expert. Most of the time there is because of communication problem. Then, we thought of something like that, where farmers don't need to go to any expert. They can detect the disease by themselves using their phone or computer browser. This will be very helpful for them to make the best production of Betel leaf and increase the production rate which will decrease the rate of loss. By using this they can take any immediate action to the affected leaf.

1.4 Expected Output

This research project can identify the diseases of betel leaf and also can increase the detection rate.

1.5 Report Layout

There are six chapters in this research paper. They are: Introduction, Background, Research Methodology, Experimental Results and Discussion, Limitations, Conclusion, Implication for Future Study.

Chapter 1: Introduction; Introduction, Motivation, Rationale of the Study, Expected Output, Report Layout.

Chapter 2: Background; Introduction, Literature Review, Research Summary, Scope of the Problem, Challenges.

Chapter 3: Betel leaf disease and symptoms; Introduction, Discussion of diseases, Survival and spread.

Chapter 4: Research Methodology; Introduction, Research Subject and Instrumentation, Data Collection Procedure, Inception V3 Model, Implementation Requirements.

Chapter 5: Experimental Results and Discussion; Introduction, Experimental Results, Confusion Matrix, Descriptive Analysis, Summary.

Chapter 6: Limitations, Conclusion, Implication for Future Study; Limitations, Conclusions, Implication for Future Study.

CHAPTER 2

BACKGROUND

2.1 Introduction

Every year our country needs to Export a large amount of Betel leaf in different countries. But most cases this because our farmers cannot produce Betel leaf or they are lack of Betel leaf because proper caring.

Disease harm to Betel leaf can significantly lessen yield. They are essentially brought about by microbes, infections, or growths. In the greater part of the cases the ailments make visual side effects, fundamentally making spots or changing shading on the leaf body, tip or stem of Betel leaf. The most widely recognized diseases of Betel leaf will be Leaf stem, Leaf Spot or Anthracnose, Bacterial leaf spot. Leaf decay brought about by *P. palmivora* and leaf spot and anthracnose brought about by *Colletotrichumcapsici*. For applying machine vision put together sickness acknowledgment based with respect to visual side effects, this study centers around three maladies named Betel leaf stem, Betel leaf Spot or Anthracnose, Bacterial leaf spot.

2.2 Literature Review

The utilization of machine vision methods have expanded comprehensively in the farming business in most recent couple of years, particularly in the plant insurance field which eventually prompts crops the executives. In [2], author's implemented Otsu thresholding based image processing algorithm for segmentation of leaf rot diseases in betel vine leaf. Twelve betel vine leaves were chosen for this work. This contained three vital stages- image acquisition, image preprocessing and segmentation. The results showed a promising performance.

In [3] authors proposed to identify powdery mildew disease in the betel vine plants using digital image processing and pattern recognition methods. They collected the betel vine leaves at different stages of disease using a high resolution digital camera. To analysis the leaves they used MATLAB. They also used RGB encoding system by which the red, green and blue components of the image were separated. After that, they computed the mean and median values for all sample leaves and test leaves. By comparing those stored values finally they identified whether test leaves were affected or not. In this paper [4], authors identified Blast and Brown Spot diseases using global threshold method and KNN classifier. At first, they collect leaf images by digital camera and then RGB images are converted into HSV color images. For segmentation, they used Otsu segmentation method with global threshold. Authors have used KNN classifier for classification and by this method they got 76.59% accuracy. In this work [5], authors proposed for leaf disease identification on randomly collected leaf images. They used ring projection method for feature extraction and after this they applied PNN classifier to recognize the leaf disease. They got 92% of recognition rate in testing phase. In this paper [6], disease detection and classification has been done. They used Convolutional Neural Network (CNN) model and Learning Vector Quantization (LVQ) algorithm based method for detect four types of diseases of tomato leaves. The proposed method effectively recognized diseases and they got 86% accuracy. [7], This paper presents the data arranged in a pro system for organizing plant infection which assessment from reaction on mango leaves. The data based got by data mining technique used decision tree model. The dataset include 129 leaf picture attributes which ordered into 3 answer classes (Normal leaf, Anthracnose, Algal Spot). After execution of J48 computation on Weka 3.8, the decision tree model shows 6 of huge features to use for organize leaf symptom. The accuracy of the model is about 89%.

According to the paper [8], thresholding and Gaussian sifting for picture preprocessing. To fragment the leaf zone, the K-means clustering procedure is utilized for division of image by at that point join extraction is finished utilizing the two surfaces too as disguising highlights. By then at last SVM game-plan framework is utilized to perceive the sort of leaf infection. In the test two classes of grape leaves were considered explicitly, Downy Development and Powdery Mildew. The given framework gives 88.89% conventional exactness for both Downey and Powdery grape leaf affliction.

2.3 Scope of the Problem

- As most of the farmers are not so educated, it could be difficult to use the system to detect the betel leaf diseases.
- The prototype is developed by using Tensorflow.

2.4 Challenges

The main challenge towards to us was collecting data on different Betel leaf diseases. Then we faced some difficulties to integrate tensorflow trained model with Anaconda and make it working. As we didn't work with web framework before it was difficult to make it working.

CHAPTER 3

BETEL LEAF DISEASE AND SYMPTOMS

3.1 Introduction

Betel leaf disease is most harmful effect for all the betel leaf farmers. If one betel leaf is become affected the chances of affect all the betel tree. It's very difficult to farmers to cope with the effect of betel tree. Every year most of the farmers faced this problem. The fungus assaults the plants at all phases of yield development. Starting indication is unexpected shrinking of plants. The influenced plants show yellowing and hanging of the leaves from tip downwards. The leaves become dull because of loss of radiance. The influenced plant evaporates totally inside 2 or 3 days. The delicious stem turns earthy colored, weak and dry as stick. The lower segment of the stem close to the dirt level shows sporadic dark sores up to second or third inter node. Ailment harm to Betel leaf can incredibly diminish yield. They are predominantly brought about by microbes, infections, or parasites. In the greater part of the cases the maladies make visual side effects, essentially making spots or changing shading on the leaf body, tip or stem of Betel leaf.

In our field research we found three types of diseases Betel leaf stem, Betel leaf spot, Bacterial leaf spot.

3.2 Discussion of diseases

Betel leaf Stem disease symptoms:

Most damaging parasitic infection that delivers a wet decay indication on leaves. From the outset round, dull earthy colored spots which become wet and decay under consistent high moist conditions. In any case dull earthy colored necrotic spots with interchange light earthy colored show up.

Survival and spread:

Fungus survives due in sickness plant garbage just as soil. These plants may recuperate after the rain and make due for multiple seasons till the root disease finishes in neckline decay and demise of the plant.



Figure 3.1: Betel Leaf Stem

Betel leaf Spot or Anthracnose diseases symptoms:

The leaves show little dark round spots at first which later grow and create to a size of 2 cm in size, gotten concentric and secured with a yellow radiance. The influenced leaves turn light yellow and evaporate with enormous dark dabs in the focal point of the spots. Dark, round injuries may create on the stem, develop quickly and griddle the stem bringing about wilting and drying.

- Leaf spots are sporadic fit as a fiddle and size, light to dull earthy colored encompassed by diffuse yellow radiance.
- Marginal leaf tissue gets dark, necrotic and continuously spreads towards the leaf place.
- Occasionally diffused yellow radiance additionally creates.
- In the anthracnose stage round, dark sores that happen quickly increment in size and support the stem finishing in the demise of the plant.

Survival and spread:

- The essential contamination by planting tainted seeds and auxiliary by wind.
- Rain and high humid.



Figure 3.2: Betel leaf Spot or Anthracnose

Bacterial leaf spot disease symptoms:

The sickness starts as minuscule, earthy colored water splashed spots on the leaves encompassed by a yellow radiance, which develop later and get necrotic and rakish, generally kept to interval zones. The tainted leaves free their radiance, turn yellow, show shrinking and tumble off. Under wet climate condition, disease spreads to stem indicating little stretched dark injuries on lower hubs and bury hubs. These injuries increment in size in the two headings and darkening May spreads to the length of a few hubs. The stem tissues become frail and break effectively at the tainted hubs and the plant show shrinking and drying.

- Minute water drenched injuries show up on everywhere on over the leaf edge which delimited by plants.
- These mix to form enormous sporadic earthy colored spots.
- The influenced leaves defoliate rashly.

Survival and spread:

- The pathogens make due in soil, Bacteria spread through water system water.
- High temperature and high relative dampness favor the advancement of malady.



Figure 3.3: Bacterial Leaf Spot

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

In Bangladesh revealed 7 Betel leaf diseases, including two viral, 2 bacterial, 2 fungal, deficiency problem of these diseases. All appeared as major during the period under report. The diseases were common in all three seasons. We went to take data from the field, for this reason all the data set taken properly. All the disease increased in rainy season. Bacterial and fungal causes most of the diseases. We have taken more than 2500 images. Image segmentation is the process of separating the objects present in the image.

4.2 Research Subject and Instrumentation

As our objective is to distinguish Betel leaf disease detection utilizing tensorflow image classifier then we utilized Python to utilize it successfully and utilize it. We utilized convolutional neural organization model to characterize pictures dependent on various infections. We have prepared our convolutional neural organization model more than 160 pictures on four distinct diseases.

Convolutional Neural Network

Deep Learning is a category of machine learning that has consecutive layers. Each layer utilizes the yield of the past layer as input. Here in this study, we use CNN as a deep learning technique.

CNN is an Artificial Neural Network which can easily classify images or objects. It is widely used in image processing and recognition, natural language processing. It has multiple layers- convolution layer, ReLU(Rectified Linear Unit) layer, pooling layer and fully connected layer.

A. Convolutional Layer

Convolution layer is the principal layer of CNN where we convolve the image utilizing channels. Channels are little units that we apply over the information through a sliding window. The convolution activity includes taking the component insightful result of channels in the image and afterward adding those qualities each sliding activity. The yield of the convolution of a 3d channel with a shading image is a 2d grid. Figure 3 shows an activity of convolution layer:

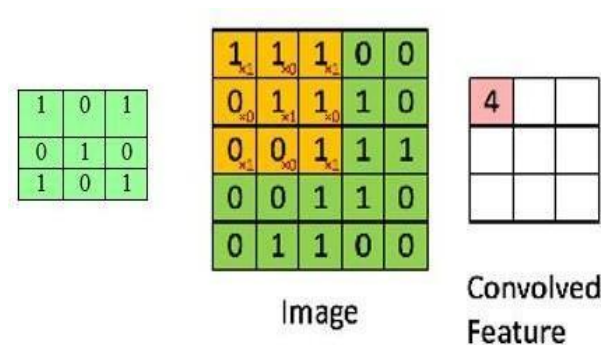


Figure 4.1: Convolution Operation

B. Pooling Layer

After completing the convolution layer, we apply the pooling layer. Numbers of features are reduced in this pooling layer. There are two hyper parameters- first is the dimension of the spatial extent and another one is stride. A typical pooling layer utilizes a 2x2 max channel with the step of 2. This is a non-covering channel. A maximum channel restores the most extreme incentive among the highlights in the districts. The profundity of the element map in the wake of pooling will stay unaltered. Performing pooling lessens the odds of over fitting as there are fewer boundaries.

Figure 4.2 shows an operation of pooling layer.



Figure 4.2: Max Pooling

C. Activation Layer

Only nonlinear initiation capacities are utilized between ensuing convolutional layers. There are many activation functions but in CNN there normally used the nonlinear ReLU(Rectified Linear Unit). In ReLU, if values are greater than zero then it will be unchanged and if values are less than zero then it will be changed to zero.

$$f(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{otherwise} \end{cases}$$

D. Fully Connected Layer

The yield from the convolution layer speaks to elevated level highlights in information while that yield could be smoothed and associated with the yield layer. Including a completely associated layer is a method of learning a nonlinear blend of this element. This is the last layer where there performed order.

4.3 Data Collection Procedure

We have considered regular Betel leaf infection of the various regions over the world as trial pictures. We have taken the pictures from the Rajshahi, Mohonpur region. We have considered Betel leaf infection pictures with the ecological parts. It has been seen that the proposed framework yield exactness changes regard to Betel leaf illnesses. We don't gathered pictures from web. More than 100 pictures have been downloaded on three unique infections which are Betel leaf Stem, Betel leaf spot or Anthracnose, Bacterial leaf spot.

Table 4.1: The raw betel leaf dataset

Label	Category	Number	Leaf Symptoms	Illustration
1	Leaf Spot or Anthracnose	100	Small, brownish black center circular or irregular lesions with yellowish hallow	See fig. 4.3 first row
2	Bacterial Leaf Spot	100	Minute water soaked spots; turn to angular spots yellowish halo. Later turn Black, turn yellow and fall.	See fig. 4.3 second row
3	Leaf Stem	100	Wet rot symptom on leaves, circular, dark brown spots which become wet and rot under continuous high Humid conditions.	See fig. 4.3 third row
4	Total	300		



Figure 4.3: Raw Betel Leaf Images

4.4 Implementation Requirements

The fundamental necessity for our venture is Python and Tensorflow. We have prepared our image classifier utilizing convolutional neural organization. The principle preferred position of the proposed strategy is lessening the acknowledgment time and computational intricacy by joining leaf and leaf malady recognizable proof .We prepared our classifier utilizing move learning technique dependent on Inception-v3 model which is prepared for the Google Imagenet Large Visual Recognition. We have retrained our classifier by running Python content for four unique maladies. At that point we have made a web interface utilizing Python, and Tensorflow. Utilizing this interface anybody can test their Betel leaf ailments by transferring influenced Betel leaf utilizing their advanced smart phone or any computer browser.

4.5 Inception V3 Model

Inception V3 is a 48 layer deep convolutional Neural Network. In a sequence of Deep Learning Convolutional Architectures, Inception V3 through Google is the third model. It was trained from the ImageNet using dataset of 1000 classes. ImageNet dataset was trained with more than 1 million training images. By using transfer learning, we can retrain this model with our original dataset for classification. Particularly, Inception v3 model consists of 3 parts- the primary convolutional block, inception model and classifier. The primary convolutional block used for feature extraction.

The Inception module is designed primarily based on Network-in-Network. In this module convolutions are performed in parallel and effects of every department are similarly concatenated.

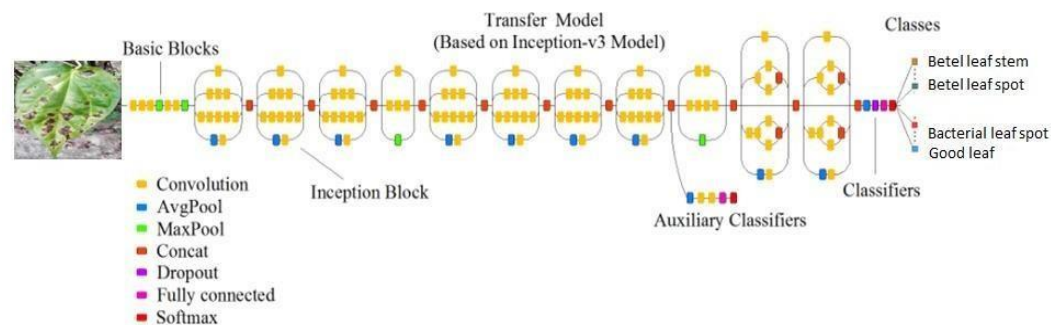


Figure 4.4: Inception V3 Model

4.6 Data Augmentation

In this study, firstly we divided the raw image dataset into 80% training samples and 20% test samples. After that the augmentation process conducted: (1) resizing all images to the size of 200x200; (2) rotating the image +30 degree; (3) rotating the image -30 degree; (4) flipping the image horizontally-about Y axis; (5) scaling the image 70%.

4.7.1 Retraining image classifier

Now image affirmation models have an immense number of limits. Setting them up without any planning requires a lot of named getting ready data and a huge amount of figuring power (a few GPU-hours or more). Move learning is a strategy that backup ways to go a great deal of this by taking somewhat of a model that has quite recently been set up on a related task and reusing it in another model. In this instructional exercise, we will reuse the component extraction capacities from astonishing picture classifiers arranged on ImageNet and simply train another request layer on top.

```
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Instructions for updating:
Use 'tf.compat.v1.graph_util.convert_variables_to_constants'
10596 16:46:15.310816 4084 retrain.py:323] From E:\tensorflow-for-poets-2-master\scripts\retrain.py:827: convert_variables_to_constants (from tensorflow.python.framework.graph_util_impl) is deprecated and will be removed in a future version.
Instructions for updating:
Use 'tf.compat.v1.graph_util.convert_variables_to_constants'
WARNING:tensorflow:From C:\Users\W\Anaconda3\lib\site-packages\tensorflow_core\python\framework\graph_util_impl.py:277: extract_sub_graph (from tensorflow.python.framework.graph_util_impl) is deprecated and will be removed in a future version.
Instructions for updating:
Use 'tf.compat.v1.graph_util.extract_sub_graph'
10596 16:46:15.324586 4084 retrain.py:323] From C:\Users\W\Anaconda3\lib\site-packages\tensorflow_core\python\framework\graph_util_impl.py:277: extract_sub_graph (from tensorflow.python.framework.graph_util_impl) is deprecated and will be removed in a future version.
Instructions for updating:
Use 'tf.compat.v1.graph_util.extract_sub_graph'
INFO:tensorflow:Froze 2 variables.
10596 16:46:15.437057 4084 graph_util_impl.py:334] Froze 2 variables.
INFO:tensorflow:Converted 2 variables to const ops.
10596 16:46:15.453181 4084 graph_util_impl.py:334] Converted 2 variables to const ops.

E:\tensorflow-for-poets-2-master>
E:\tensorflow-for-poets-2-master>
```

Figure 4.5: Retraining image classifier from terminal

```
C:\Windows\System32\cmd.exe
10596 16:45:47.256727 4084 retrain.py:1082] 2020-05-06 16:45:47.256727: Step 160: Train accuracy = 65.0%
INFO:tensorflow:2020-05-06 16:45:47.256727: Step 160: Cross entropy = 5.889703
10596 16:45:47.256727 4084 retrain.py:1084] 2020-05-06 16:45:47.256727: Step 160: Cross entropy = 5.889703
INFO:tensorflow:2020-05-06 16:45:47.377801: Step 160: Validation accuracy = 65.0% (N=100)
10596 16:45:47.377801 4084 retrain.py:1100] 2020-05-06 16:45:47.377801: Step 160: Validation accuracy = 65.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:48.087689: Step 170: Train accuracy = 73.0%
10596 16:45:48.087689 4084 retrain.py:1082] 2020-05-06 16:45:48.087689: Step 170: Train accuracy = 73.0%
INFO:tensorflow:2020-05-06 16:45:48.088692: Step 170: Cross entropy = 3.972505
10596 16:45:48.088692 4084 retrain.py:1084] 2020-05-06 16:45:48.088692: Step 170: Cross entropy = 3.972505
INFO:tensorflow:2020-05-06 16:45:48.189549: Step 170: Validation accuracy = 58.0% (N=100)
10596 16:45:48.189549 4084 retrain.py:1100] 2020-05-06 16:45:48.189549: Step 170: Validation accuracy = 58.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:48.908324: Step 180: Train accuracy = 76.0%
10596 16:45:48.908324 4084 retrain.py:1082] 2020-05-06 16:45:48.908324: Step 180: Train accuracy = 76.0%
INFO:tensorflow:2020-05-06 16:45:48.908324: Step 180: Cross entropy = 2.054757
10596 16:45:48.908324 4084 retrain.py:1084] 2020-05-06 16:45:48.908324: Step 180: Cross entropy = 2.054757
INFO:tensorflow:2020-05-06 16:45:49.012994: Step 180: Validation accuracy = 65.0% (N=100)
10596 16:45:49.012994 4084 retrain.py:1100] 2020-05-06 16:45:49.012994: Step 180: Validation accuracy = 65.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:49.728833: Step 190: Train accuracy = 82.0%
10596 16:45:49.728833 4084 retrain.py:1082] 2020-05-06 16:45:49.728833: Step 190: Train accuracy = 82.0%
INFO:tensorflow:2020-05-06 16:45:49.728833: Step 190: Cross entropy = 0.941663
10596 16:45:49.728833 4084 retrain.py:1084] 2020-05-06 16:45:49.728833: Step 190: Cross entropy = 0.941663
INFO:tensorflow:2020-05-06 16:45:49.817690: Step 190: Validation accuracy = 73.0% (N=100)
10596 16:45:49.817690 4084 retrain.py:1100] 2020-05-06 16:45:49.817690: Step 190: Validation accuracy = 73.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:50.529071: Step 200: Train accuracy = 66.0%
10596 16:45:50.529071 4084 retrain.py:1082] 2020-05-06 16:45:50.529071: Step 200: Train accuracy = 66.0%
INFO:tensorflow:2020-05-06 16:45:50.529071: Step 200: Cross entropy = 4.896437
10596 16:45:50.529071 4084 retrain.py:1084] 2020-05-06 16:45:50.529071: Step 200: Cross entropy = 4.896437
INFO:tensorflow:2020-05-06 16:45:50.621152: Step 200: Validation accuracy = 65.0% (N=100)
10596 16:45:50.621152 4084 retrain.py:1100] 2020-05-06 16:45:50.621152: Step 200: Validation accuracy = 65.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:51.324385: Step 210: Train accuracy = 71.0%
10596 16:45:51.324385 4084 retrain.py:1082] 2020-05-06 16:45:51.324385: Step 210: Train accuracy = 71.0%
INFO:tensorflow:2020-05-06 16:45:51.324385: Step 210: Cross entropy = 2.020187
10596 16:45:51.324385 4084 retrain.py:1084] 2020-05-06 16:45:51.324385: Step 210: Cross entropy = 2.020187
INFO:tensorflow:2020-05-06 16:45:51.433737: Step 210: Validation accuracy = 72.0% (N=100)
10596 16:45:51.433737 4084 retrain.py:1100] 2020-05-06 16:45:51.433737: Step 210: Validation accuracy = 72.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:52.146977: Step 220: Train accuracy = 70.0%
10596 16:45:52.146977 4084 retrain.py:1082] 2020-05-06 16:45:52.146977: Step 220: Train accuracy = 70.0%
INFO:tensorflow:2020-05-06 16:45:52.146977: Step 220: Cross entropy = 3.341661
10596 16:45:52.146977 4084 retrain.py:1084] 2020-05-06 16:45:52.146977: Step 220: Cross entropy = 3.341661
INFO:tensorflow:2020-05-06 16:45:52.250583: Step 220: Validation accuracy = 57.0% (N=100)
10596 16:45:52.250583 4084 retrain.py:1100] 2020-05-06 16:45:52.250583: Step 220: Validation accuracy = 57.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:52.957203: Step 230: Train accuracy = 80.0%
10596 16:45:52.957203 4084 retrain.py:1082] 2020-05-06 16:45:52.957203: Step 230: Train accuracy = 80.0%
INFO:tensorflow:2020-05-06 16:45:52.957203: Step 230: Cross entropy = 1.003145
10596 16:45:52.957203 4084 retrain.py:1084] 2020-05-06 16:45:52.957203: Step 230: Cross entropy = 1.003145
INFO:tensorflow:2020-05-06 16:45:53.059608: Step 230: Validation accuracy = 76.0% (N=100)
10596 16:45:53.059608 4084 retrain.py:1100] 2020-05-06 16:45:53.059608: Step 230: Validation accuracy = 76.0% (N=100)
INFO:tensorflow:2020-05-06 16:45:53.754162: Step 240: Train accuracy = 71.0%
10596 16:45:53.754162 4084 retrain.py:1082] 2020-05-06 16:45:53.754162: Step 240: Train accuracy = 71.0%
INFO:tensorflow:2020-05-06 16:45:53.754162: Step 240: Cross entropy = 4.843337
10596 16:45:53.754162 4084 retrain.py:1084] 2020-05-06 16:45:53.754162: Step 240: Cross entropy = 4.843337
INFO:tensorflow:2020-05-06 16:45:53.847956: Step 240: Validation accuracy = 56.0% (N=100)
```

Figure 4.6: Retraining image classifier from terminal

Despite the fact that it's not in the same class as preparing the full model, this is shockingly viable for some, applications, works with moderate measures of preparing information (thousands, not a great many marked pictures), and can be run in as meager as thirty minutes on a computer without a GPU. This instructional exercise will show the best way to run the model content on your own images, and will clarify a portion of the alternatives you need to help control the preparation cycle.

When the bottlenecks are finished, the genuine preparing of the top layer of the organization starts. You will see a progression of step yields, every one demonstrating preparing precision, approval exactness, and the cross entropy. The preparation precision shows what percent of the pictures utilized in the current preparing cluster were named with the right class. The approval exactness is the accuracy on a haphazardly chosen gathering of pictures from an alternate set. The key contrast is that the preparation precision depends on image that the organization has had the option to gain from so the organization can over fit to the clamor in the preparation information. A genuine proportion of the exhibition of the organization is to quantify its presentation on an informational collection not contained in the preparation information this is estimated by the approval precision. On the off chance that the train precision is high yet the approval exactness stays low that implies the organization is over fitting and retaining specific highlights in the preparation pictures that aren't useful all the more by and large. Cross entropy is a misfortune work which gives a brief look into how well the learning cycle is advancing.

The preparation's goal is to make the misfortune as little as could be expected under the circumstances, so you can tell if the learning is working by watching out for whether the misfortune continues drifting downwards, disregarding the transient commotion.

As a matter of course this content will run 4,000 preparing steps. Each progression picks ten pictures indiscriminately from the preparation set, finds their bottlenecks from the reserve, and feeds them into the last layer to get expectations. Those expectations are then contrasted against the real marks with update the last layer's loads through the back-proliferation measure.

As the cycle proceeds with you should see the revealed exactness improve, and after all the means are done, a last test precision assessment is run on a lot of pictures kept separate from the preparation and approval pictures.

This type test assessment is the best gauge of how the prepared model will perform on the grouping task. You could see a precision estimation of somewhere in the range of 90% and 95%, however the specific worth will shift from race to run since there's irregularity in the preparation cycle.

This number depends on the percent of the pictures in the test set that are given the right name after the model is completely prepared.

An average strategy for improving the delayed consequences of image planning is by contorting, tending to, or illuminating the readiness commitments to sporadic ways. This has the upside of broadening the practical size of the readiness data by virtue of the evident huge number of likely assortments of comparative images, and will all in all help the association make sense of how to adjust to all the curves that will occur, in light of everything, occupations of the classifier. The best weight of engaging these turns in our substance is that the bottleneck putting away isn't, now useful, since input pictures are never reused accurately. This infers the readiness cycle takes significantly more (various hours), so it's recommended you endeavor this as a technique for cleaning your model basically after you have one that you're reasonably content with.

4..7.2 Activity Diagram

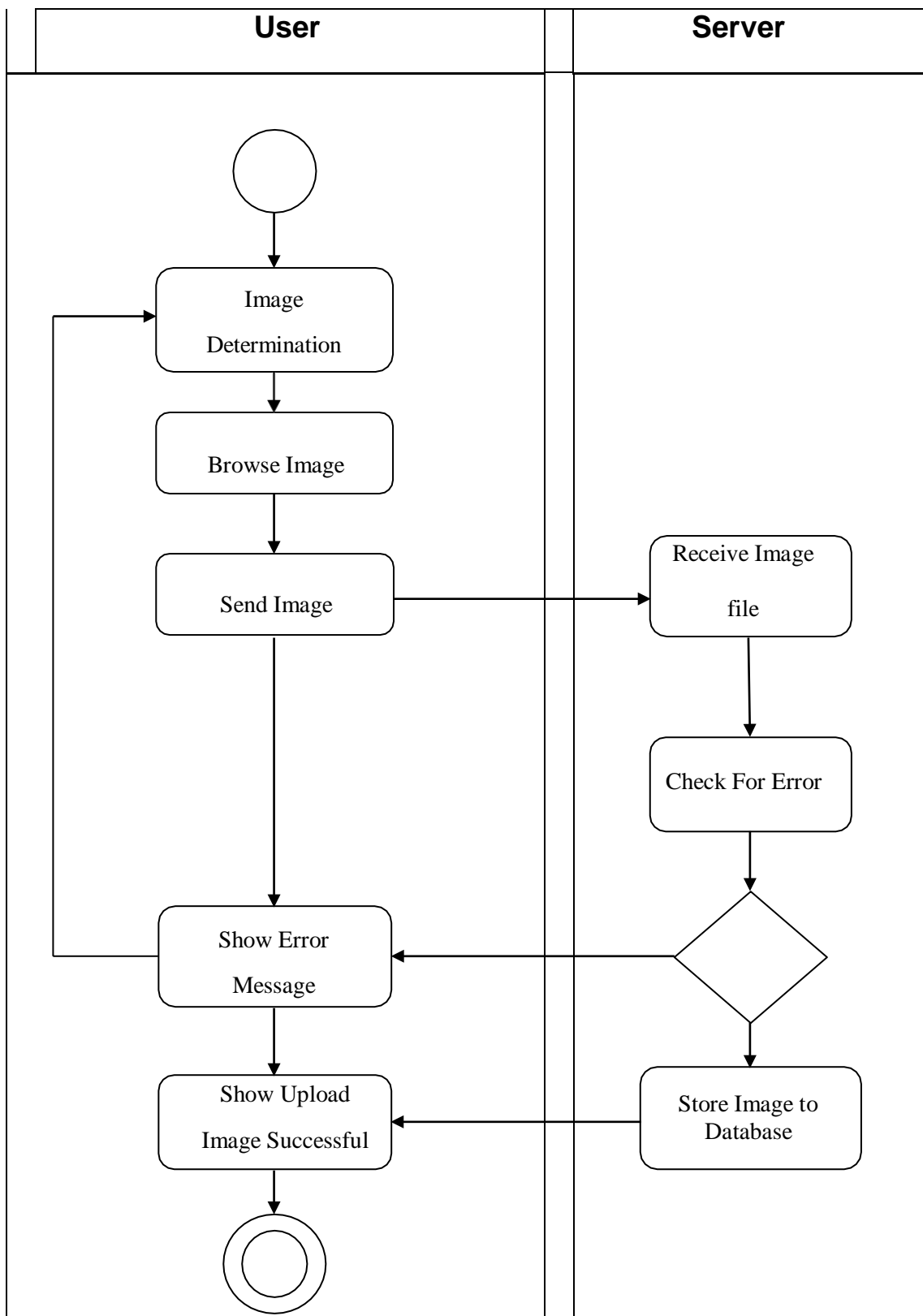


Figure 4.7: Image Upload Activity diagram.

4.8 Discussion

In this framework ranchers can get the exact data about the betel leaf sickness utilizing their smart phone or PC program. First they will take image of the betel leaf and transfer it in our framework. The transferred photos of the betel leaf will be prepared in the focal worker and it will examination in the focal worker then it will show with the ailment name the leaf has on the off chance that it matches with three disease it was prepared on.

CHAPTER 5

EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Introduction

Betel leaf disease becomes a common problem in our agriculture of Bangladesh. Many people of Bangladesh directly or indirectly depend on agriculture especially on Betel leaf. They want to produce large amount of Betel leaf to reduce the lack of Betel leaf in our country. But the main problems behind this were caring of the Betel leaf properly and detect its disease to increase the production rate.

5.2 Experimental Results

We have considered exceptionally normal Betel leaf illness of the various zones over the world as test images. We have taken the pictures from the Rajshahi, Mohonpur zone. Betel leaf malady images with the natural parts. It has been seen that the proposed framework yield precision fluctuates regard to Betel leaf disease.

We examine the trial results. All the examinations were executed in Tensorflow under Windows 10. In this paper, generally exactness was viewed as the assessment metric in each examination on betel leaf malady location, which implies the level of tests that are effectively grouped:

$$\text{Accuracy} = \frac{(\text{true positive} + \text{true negative})}{(\text{positive} + \text{negative})}$$

Where "true positive" is the quantity of occurrences that are positive and named positive, "true negative" is the quantity of cases that are negative and delegated negative, and the denominator speaks to the all-out number of tests. Also, the preparation time was viewed as an extra presentation metric of the organization structure test.

So as to play out a hearty approval and test for any characteristic predisposition in the datasets, tests were run for a scope of preparing testing information parts. During model preparing, 10% of the dataset was utilized to approve preparing steps, accordingly 90% of the dataset was part into various preparing and testing dataset designs.

The preparation test parts were as per the following: 80-10 (80% of dataset for preparing, 10% for testing separately), 60-30 (60% of dataset for preparing, 30% for testing individually), 50-40, (half of dataset for preparing, 40% for testing individually), 40-50 (40% of dataset for preparing, half for testing individually), and 20-70 (20% of dataset for preparing, 70% for testing individually). For each test the general exactness is accounted for as the quantity of tests in all classes that were comparable.

These outcomes show that datasets expected to fabricate move learning models for plant illness conclusion don't need exceptionally huge preparing datasets (<500 pictures per class). The high exactness's announced propose that varieties in foundation had little impact on the expectation correctness's of the model. Segments of pictures contained the sky, hands, shoes, and other vegetation, yet expectations in all picture classes were incredibly over the likelihood of arbitrarily speculating (16.7%). In the field all things considered, an augmentation specialist would utilize more than one picture to anticipate the infection, consequently improving the indicative exactness further. This examination subsequently shows that move learning applied to the Inception v3 profound learning model offers a promising road for in-field illness recognition utilizing convolutional neural organizations with moderately little image datasets.

5.3 Confusion Matrix

Table 5.1: Confusion Matrix

	Bacterial leaf spot (prediction)	Leaf spot (prediction)	Stem leaf (prediction)
Bacterial leaf spot (Actual)	60	2	3
Leaf spot (Actual)	5	56	4
Stem leaf (Actual)	5	0	60

True positive for Bacterial leaf spot: 60

True positive for Leaf spot: 56

True positive for Stem leaf: 60

True negative for Bacterial leaf spot: 65+60+61

True negative for Leaf spot: 65+60+61

True negative for Stem leaf: 65+60+65

False positive for Bacterial leafspot:10

False positive for leaf spot: 2

False positive for Stem leaf: 7

False negative for bacterial Leaf spot:5

False negative for Leaf Spot: 9

False negative for Stem Leaf: 5

Accuracy for Bacterial leaf spot: $60/65=.92$

Accuracy for Leaf spot: $56/65=.86$

Accuracy for Stem leaf: $60/65=.92$

Total Accuracy = $(60+65+60)/100= 0.90$

Precision for Bacterial leaf spot: .85

Precision for Leaf spot: .96

Precision for Stem leaf: .89

Total Precision: .90

Recall= $(tp)/(tp+fn)$

Recall for Bacterial leaf spot: .0.92

Recall for Leaf spot: . 8 6

Recall for Stem leaf: .92

Total recall = .90

F1 score= $2*((precision*recall)/(precision+recall))$

=0.90

5.4 Descriptive Analysis

The GoogleNet design then again is a lot further and more extensive engineering with 22 layers, while as yet having significantly lower number of boundaries (5 million boundaries) in the organization than AlexNet (60 million boundaries). An utilization of the "network in network" design as the beginning modules is a key element of the GoogleNet engineering. The initiation module utilizes equal 1x1, 3x3 and 5x5 convolutions alongside a maximum pooling layer in equal, subsequently empowering it to catch an assortment of highlights in equal. Regarding common sense of the

usage, the measure of related calculation should be held in line, so they include 1x1 convolutions before the previously mentioned 3x3, 5x5 convolutions (and furthermore after the maximum pooling layer) for dimensionality decrease.

Finally, a channel connection layer just links the yields of all these equal layers. While this structures a solitary initiation module, a sum of 9 origin modules is utilized in the variant of the GoogLeNet engineering that we use in our analyses. We dissect the presentation of both these designs on the PlantVillage dataset via preparing the model without any preparation in one case, and afterward by adjusting effectively prepared models (prepared on the ImageNet dataset) utilizing move learning.

5.5 Summary

The consequences of this examination show that picture acknowledgment with move gaining from the convolutional neural organization Inception v3 is an incredible strategy for high exactness computerized Betel leaf disease location. This technique evades the complex and work serious advance of highlight extraction from images so as to prepare models, and the model can be effectively prepared on a work area and sent on a smart phone. Move learning is additionally equipped for applying normal AI strategies by retraining the vectors created by the prepared model on new class information.

CHAPTER 6

LIMITATIONS, CONCLUSION, IMPLICATION FOR FUTURE STUDY

6.1 Limitations

We have thought about not many constraints of the framework. First disadvantage of this undertaking is that we have restricted foundation in agribusiness study, so understanding the issue or infection was a test for us. Another disadvantage would be the calculation which drops the foundation for picture investigation of Betel leaf illness has restrictions. On account of the undesirable foundation of the image, it probably won't show promising or precise outcomes. In the underlying advancement of this undertaking we confronted many test with respect to this issue. For now we permitted the client to choose just on the malady influenced choices utilizing Nokia picture zooming and crop capacities. Notwithstanding, if the malady happens in the tip or side of the Betel leaf leaves, it is important to consider applying foundation retractions methods. What's more, the framework is created in English which will be practically unimaginable for the vast majority of our ranchers as our rancher living the provincial region are not instructed enough.

6.2 Conclusions

This research focuses on recognizing betel leaf ailment utilizing profound convolutional network by transfer learning. The dataset comprise of 400 betel leaves pictures. We prepared our classifier utilizing move learning technique dependent on Inception-v3 model which is prepared for the Google Imagenet Large Visual Recognition. We have retrained our classifier by running Python content for three distinct ailments. Thusly, by actualizing the method betel leaf infections are perceived around 90 percent exactness rates. The tests have been completed on solid and ailing leaf pictures for order. It is reasoned that the proposed strategy viably perceives three distinct sorts of infections. We accept this promising outcome provides us future guidance for a powerful application, making more viable apparatus that everything ranchers can use for the executives all harvests.

6.3 Implication for Future Study

We have intended to refresh this framework for usage of the task, in actuality. We have an arrangement that after updating this framework the ranchers particularly the ranchers living in the distant region of the nation will get help effectively and can take care of their concern with less exertion. The essential focal point of our venture is to conquer the impediments of the current created framework. Our Background crossing out calculations should be applied for the image preparing to work for any image. Notwithstanding that, smartphone, camera and web.

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